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Abstract

Beverage consumption occurs many times a day in response to a variety of needs that change throughout the day. In making their choices, consumers self-regulate their consumption by managing short run needs (e.g., hydration and mood pickup) with long-term goals (e.g., health). Using unique intra-day beverage consumption, activity and psychological needs data, we develop and estimate a model of high frequency consumption choices that accounts for both intra-day changes in short run needs and individual level unobserved heterogeneity in the degree of self-regulation. A novel feature of the model is that it allows for dynamics of consumption and stockpiling at the level of product attributes. The model is used to evaluate introduction of new products in the beverage category and gain insight into the linkage between self-regulation and excess consumption. Broadly, the modeling framework of balancing short run needs with long-term goals has wide ranging applications in choices where long term effects are gradual (e.g., nutrition, exercise, smoking and preventive health care).

Key Words: Dynamic discrete choice, EM algorithm, self-regulation, stockpiling, health care, needs, goals, obesity, beverages, new product introductions.

1 Introduction

Every day, many times a day, individuals make choices about what to drink. The decision to consume a beverage is driven primarily by thirst—among the most basic of human needs. Yet like many other consumption decisions, the choice of a beverage lies on a continuum from satisfying the bare utilitarian need to hydrate, to something more hedonic like enhancing one's mood. One could drink just water to hydrate and satiate thirst, but the choices individuals make are also affected by other contemporaneous situational factors that drive their short-term needs; for example, a pick-up to enhance mood, a stimulant to help focus, or a relaxant to relieve stress. Importantly, these routine choices made several times a day and accumulated over time also have significant long-term consequences. For example, routine consumption of drinks with excess calories can cause weight gain and increase the risks for cardiovascular and other diseases such as diabetes over the long run (see e.g., Malik et al. 2006, Vartanian et al. 2007, Mozaffarian et al. 2011). Individuals therefore seek to self-regulate and manage their response to short-term needs against long-term goals such as health and nutritional well-being.

The goal of this paper is to introduce a framework to model individual short-run choices with long-term consequences. To that end, we develop and estimate a dynamic model of thirst, 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.[1] The model allows consumers to differ in their ability to self-regulate the balance between the short-term and long-term, and hence incorporates unobserved heterogeneity on this dimension. We estimate the model using unique intra-day data on actual beverage consumption as well as the attendant occasion specific activity, social context and short-run needs of a large nationally representative panel of

[1] Industry reports suggest that firm segmentation strategies in the beverage industry recognize this tradeoff between short-run needs and long-term attitudes and goals. For example, "The U.S. Beverage Universe," a report by TNS Landis notes that "consumers experience a variety of consumption occasions throughout their day, driven by a unique bundle of occasion specific requirements, features and emotional benefits" and "every consumer is motivated by attitudes towards life, food and health that…influence how they interact with food and beverages, and pre-dispose them to make the choices they make." (For more information see www.TNS-Landis.com).

households and perform counterfactuals that serve to guide segmentation strategies and new product introductions in the beverage market.[2] The approach we develop is applicable in many settings where routine short-run choices have both positive and negative long-run consequences. For example, our framework can be useful in modeling routine consumer choices such as preventive care (or lack of it), exercise and smoking that have long run consequences like cardiovascular disease and cancer respectively.[3]

There is a long history of research in marketing that has focused on modeling choice at the point of purchase. Beginning with the pioneering work of Guadagni and Little (1983), there is now a large volume of work both in marketing and economics on 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 research on choice at the point of consumption.[4] In categories like detergents, the distinction between purchase and consumption may be moot, because households 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 category 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 category. 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? A deeper understanding of the factors that drives consumption of different categories of beverages at the point of consumption is critical for firms competing for "share of thirst."

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[2] The beverage market is large with annual 2007 sales of $88 billion and shared between many sub-categories: the 2008 markets shares were carbonated soft drinks (48%) bottled water (29%), fruit beverages (13%), sports drinks (4.4%), ready-to-drink tea (2.9%), flavored & enhanced waters (1.8%), energy drinks (1.2%) and ready-to-drink coffee (0.2%). The competition for "share of thirst" is intense with large changes in category shares over time: for example, per-capita consumption of milk fell from 31 gallons in 1970 to 7.6 gallon in 2003, while sodas gained from 24 gallons to 46.4 gallons during the same period, with diet sodas rising from 2 gallons to 11.1 gallons.

[3] For another approach based on using field experiments to examine such long run effects, see e.g., Dupas (2012).

[4] To be sure, there is much work on consumption choice in the behavioral literature, because there is little distinction between whether one asks about purchase or consumption in experimental work; they are all clubbed as "choices." See e.g., the comprehensive set of articles in Ratneshwar and Mick (2005).

There are several challenges in modeling beverage consumption. The first is the frequency of consumption. Because beverage consumption occurs multiple times and the choice of beverage varies widely even within the day for an individual, one needs high frequency intra-day consumption data. Researchers traditionally make inferences about consumer's utility from consumption thorough weekly purchase data, but as described earlier, such data is not very useful in modeling beverage consumption.

Second, beverages are consumed in tandem with activities such as eating (breakfast, lunch, dinner), work, parties or exercise. The social environment differs across these activities and even within these activities. Some eating occasions are solitary, others happen with family or friends, and others with 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. Since needs change from one consumption occasion to the next, an individual level model that treats needs to be stable across consumption occasions is simply not an accurate representation of the individual and would explain consumption choices very poorly. Hence, one requires information about the contemporaneous needs that an individual seeks to satisfy during each potential consumption occasion.

Third, as discussed earlier, unlike most consumer choices where the utility from the product is modeled as immediate,[5] beverage (and food) consumption have long-term health consequences and these consequences accrue very gradually. Consumers therefore balance their short-run needs with long-term goals, but they differ in the degree to which they self-regulate to maintain this balance. Therefore the modeling approach needs to accommodate heterogeneity in the degree of self-regulation by consumers.

We address these challenges through a combination of new data and modeling. We address the first two challenges due to high frequency intra-day consumption and the variation in needs

[5] Long-term dynamics and forward-looking behavior in such models focus around timing of purchase and stockpiling in response to price promotions.

and preferences for beverages across consumption occasions directly through better data. For this, we use unique "consumption diary" data on a panel of individuals. Using PDAs that alert consumers to record consumption eight times during a day (every two hours during the 16 hour waking period of a day), we have consumption choices and contemporaneous information such as activity, social setting and "needs" associated with the consumption occasion over a period of two weeks.[6]

We address the issue of heterogeneity in how individuals self-regulate[7] in balancing their short-run and long-term needs by allowing three types of "as-if" behavior.[8] First, we consider an "impulsive" individual, who does not self-regulate at all, and therefore choice is driven entirely by contemporaneous needs and level of thirst (modeled as a stock variable that evolves based on how long it has been since the individual drank a beverage). This impulsive behavior is modeled as a random utility logit model, where choices are explained by contemporaneous needs and the dynamic thirst stock. Second, we consider an "adaptive" individual who partially self-regulates by adapting current choice in response to past consumption choices. For example, such a person might forego coffee at 10 A.M. because he already had coffee for breakfast. Such adaptive behavior is also modeled as a random utility logit model like for the impulsive type, but with an additional state dependence term that accounts for past choices. Finally, we consider an "anticipatory" individual, who exhibits the highest level of self-regulation by not only adapting to past choices, but also in anticipation of future needs. For example, an individual expecting to consume

[6] A small literature has focused on modeling consumption activities. Luo, Ratchford and Yang (2011) analyze activity choices and time allocation decisions of consumers using observational data at a weekly level. They focus on how consumption leads to accumulation of expertise in activity, and leads to concentration of activities across time. However, they do not model forward-looking behavior. Yang, Allenby and Fennell (2002) examine the static effects of the social environment and psychological motivations on brand preference for beer. Their analysis is based on a conjoint style survey where consumers are assigned to different social environments and then asked to state their preferences for different types of beers under the different environments.

[7] There is a large body of research in on self-control, goal setting and self-regulatory behaviors, e.g., Mischel, Shoda and Rodriguez (1989), Ainslie (1992), Laibson (1997), Frederick, Loewenstein and O'Donoghue (2002), Health, Larrick and Wu (1999), Rachlin (2000) and Trope and Fishback (2000). Our definition of "self-regulation" is self-explanatory and self-contained within the context of our model as described below.

[8] See Houser, Keane and McCabe (2004) for a similar approach to modeling heterogeneity in decision making abilities.

unhealthy foods at a party later in the day may choose healthier options earlier in the day. We model anticipatory behavior using a dynamic forward-looking model whose current utility follows a random utility logit model with state dependence.

Our forward-looking model may be compared and contrasted relative to extant models in the literature. We allow for the stock of "thirst" to be endogenous to past beverage consumption decisions. Thus we allow for dynamics in both consumption and stockpiling. The thirst stock is similar to the inventory variable in dynamic structural models of stockpiling (see e.g., Erdem, Imai and Keane 2003, Hendel and Nevo 2006). Further, products are modeled as bundles of attributes ("healthy," "unhealthy", "mood-enhancing" and "hydrating"). A unique feature of the model is that we allow for dynamics in the consumption and stockpiling at the attribute level. This feature is particularly relevant when examining the effects of introduction of new products which are defined as innovative bundles of attributes (see, e.g., Petrin 2002 for a static model). 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 or conversely the effects of expectations about future health on current decisions in a model of daily decision making. Another novel aspect of the model that helps to incorporate such effects is that we implement long-term goals as a heuristic or rule-of-thumb, in particular, an end-of-day salvage value for avoiding consumption of too many unhealthy drinks in a day.

To estimate the model with unobserved heterogeneity in self-regulation, we use an EM algorithm (see e.g., Arcidiacono and Jones 2003). The algorithm starts with an initial probability for each household belonging to each of the three self-regulation segments; at each iteration of the algorithm, we use a Bayesian procedure to calculate the posterior probability that each individual falls in to one these three segments; we iterate until the probabilities converge. Unlike the Kamakura and Russell (1989) latent class approach, which assigns the same segment probability for all individuals, we allow each individual to have a different segment probability that is consistent with his/her string of consumption choices. As discussed earlier, we model time varying preferences directly as observable "need-states" from the data. An alternative approach is to treat these time varying preferences as unobserved heterogeneity within individuals through preference switching models as in Arcidacono and Miller (2011). While this is feasible when there are a few switching states, the approach is not feasible in our setting to identify preference switching across the large combination of occasions and "need-states."

We use our estimated model to perform various counterfactuals relevant to consumers, health policy makers and managers in the beverage industry.[9] Using the estimated parameters we simulate: (i) the effect of new product introductions (e.g., vitamin-enhanced water that adds health benefits to water) and (ii) the differential effect of changes in schedules and activities, (e.g., a series of parties during the holiday season) on the consumption of individuals of different self-regulation types. The first counterfactual analyzes the potential for new product introduction, e.g., gain in market shares in different segments, category expansion or business stealing. The second counterfactual examines how individuals of different degrees of self-regulation change their beverage consumption in response to shocks to activities which in turn affect need states and consumption.[10] From a firm's segmentation perspective, this can help understand the type of individuals one should target in order to drive increased consumption during peak demand periods such as holidays. From a policy perspective, this can help assess whether there is value in

[9] There is growing interest in such issues among consumers, policy makers and beverage manufacturers. For anecdotal evidence of: (i) increased interest among firms in introducing healthier products, see e.g., "Dr Pepper Slims Down Five More of Its Sodas," by Paul Ziobro, *The Wall Street Journal*, December 3, 2011, "PepsiCo's Health Push," by Megha Bahree and Mike Esterl, *The Wall Street Journal*, July 7, 2011, (ii) growing competition in the category of healthier beverages, see e.g., "The Beverage Wars Move to Coconuts," by Mike Esterl, *The Wall Street Journal*, February 11, 2012, and (iii) recent policies being considered to promote consumption of healthier beverages, see e.g., "Bottlers Agree to a School Ban on Sweet Drinks," by Marian Burros and Melanie Warner, *The New York Times*, May 4, 2006, "New York Asks to Bar Use of Food Stamps to Buy Sodas," by Anemona Hartocollis, *The New York Times*, October 6, 2010, "Experts Urge Testing of Ban on Use of Food Stamps for Soda," by Patrick McGeehan, *The New York Times*, September 27, 2011.

[10] With the rising trends in obesity and related health risks the subject of food consumption, time use and self-regulation has received a lot of attention recently (e.g., Cutler et al. 2003, Bertrand and Schanzenbah 2009). Alternative approaches that have been employed to analyze these issues include among others, e.g., Thaler and Sunstein 2008, Downs, Loewenstein and Wisdom 2009, Wansink, Just and Payne 2009, Dobson and Gerstner 2010, Thomas, Desai, and Seenivasan 2011, Jain 2012, and Thorndike et al. forthcoming.

potentially changing the self-regulating behavior of consumers through education and advertising strategies in order to encourage healthy consumption.

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

2 Data

Our data comes from a nationally representative panel of 2683 individuals whose beverage consumption decisions are tracked for two weeks. The data was collected by giving individuals a handheld device that prompted them eight times a day for two weeks to answer a host of questions regarding any beverage consumption in the previous two hours, e.g., the type of beverage consumed, the time of day, the location and social setting, the psychological motivations for choosing the beverage etc.

There are 16 types of drinks in the data, such as coffee, tea, milk, etc. For our analysis, we define the following four binary attributes for the drinks: healthy, unhealthy, mood-boosting and hydrating according to aggregate consumer opinion.[11] Table 1 shows the binary attributes for the 16 types of drinks. Based on the four attributes, the original 16 drinks can be grouped into six categories, as shown in Table 2. Motivated by our interest in the health implications of beverage consumption and choices we observe in the data, we focus on consumers' consumption decisions on the six categories of drinks.

For the purpose of estimating the model, we drop observations of people who do not drink any healthy or unhealthy drinks, given our interest in studying the balance between short-run

[11] For this purpose, we first compute the percentages of consumers that think of each of the drinks as healthy, mood-boosting and hydrating. Then, we compute the averages of the three percentages across the 16 drinks, and the standard deviations of the three averages. Finally, we define the three attributes (healthy, mood-boosting and hydrating) of a drink to be one if and only if its percentages are above the respective average percentages plus 3 times the standard deviations of the averages. And we define the unhealthy attribute of a drink to be one if and only if the percentage of consumers that think it healthy is below the average minus 3 times the standard deviation of the average percentage.

needs and long-term health goals. This leaves us with an estimation sample of 2350 individuals. We use data from Monday-Thursday of one week for estimation. We exclude data from weekends and Fridays, because the weekend and Friday consumption patterns are systematically different from weekday consumption. We exclude the first period (before breakfast) and the last period (late night) because very few people drink anything at those times. We use data from Monday-Thursday of the second week to calibrate individual specific controls for the number of healthy and unhealthy drinks (we describe the controls later). In all, there are a total of 56400 observations for estimation.

The daily total beverage consumption varies by drink categories. In our data, relatively few people drink more than one healthy drink a day, most of which is consumed during breakfast. In comparison, it is common for individuals to have multiple unhealthy drinks. The variation in unhealthy drink consumption is large. Across the sample, individuals drank only one unhealthy drink on 36 percent of the days; and at least 3 unhealthy drinks on 14 percent of the days. Such large variation can have important implications for consumers' long-term health.

We group occasions or activities at time of consumption into six categories, such as eating, work, TV etc., as shown in Table 3. Table 4 shows the share of activities during different times of the day. Eating is prominent during breakfast, lunch and dinner; work is prominent during morning and afternoon; while TV is prominent during the evening. Table 5 shows that beverage consumption is closely associated with occasions. Eating and watching TV are the two major drivers of beverage consumption. Furthermore, the selection of beverage categories is also linked to occasions. At the extreme, people drink mostly unhealthy/mood-boosting drinks when they are at a party. People also drink more unhealthy drinks than any other categories while they are watching TV. We summarize the impact of occasion on consumer preference for beverages using three factors or psychological "needs": hydrate, health and mood. The "needs" reflect three main psychological motivations underlying consumers' beverage consumption decisions. The three needs are constructed using factor analysis based on the answers to 18 survey questions asking why consumers chose their drinks.[12] Figure 1 shows the mean of the three need factors conditional on each of the six occasions. The three need factors vary a lot by occasion. The health need is relatively high while eating; the mood need is high for party and relax occasions; the hydration need is very high during exercise.

Finally, the data also shows large variation in people's propensity to drink (see Table 6). First, consumers differ by the observed maximum number of consecutive periods without drinking anything. While the median number of drinks in a day is 4, and the 25%-75% inter-quartile ranges from 3 to 5. Similar pattern can also be seen also through the maximum daily consumption of unhealthy (and healthy) drinks. The median numbers for maximum number for healthy and unhealthy drinks are 2 and the 3. The 25%-75% interquartile range for healthy drink is 1 and 2. The corresponding numbers for unhealthy drinks are 2 and 4. Overall, we see much greater variation in the number of unhealthy drinks. To control for such *observed* heterogeneity, in consumption behaviors we use the maximum daily consumption of healthy and unhealthy drinks as control variables in a consumer's per-period utility function.

3 Model of Intra-Day Decisions and Self-Regulation

In this section, we describe our formal dynamic model of intra-day beverage consumption decisions. We capture the following features of beverage consumption behavior on a typical day in the model. First, it accounts for short-run contemporaneous needs in the utility function, allowing for diversity in choices across different occasions. We model consumption in a random utility logit framework with stochastic preferences that are related to the consumer's social and physical environment and activities. Second, it accounts for (endogenous) accumulation of thirst similar to endogenous modeling of inventory in forward looking stockpiling models (in the presence of price

[12] At each consumption occasion a consumer was asked "why the drink was chosen?" and the consumer could respond with one or more of the following 18 possible reasons: (1) Change of pace, (2) Cool off, (3), (4) Warm up, (5) Mood enhancer, (6) Filling, (7), Fortified with vitamins, (8) Fruit flavored, (9) Fun to drink, (10) Goes well with food, (11) Good for physical activity, (12) Good for social situations, (13) Indulgent/treat, (14) Nutritional/healthy, (15) Portable, (16) Quick energy/pick-me up, (17) Re-hydrating, and (18) Nearest/closest.

promotions). We model the thirst stock as the number of consecutive periods that a consumer has gone without drinking until the current period.

Third, the model incorporates two aspects of self-regulating behavior. One, it accounts for adaptive (backward looking) responses that take into account the health effects of past consumption; here we include the total number of each kind of (e.g., healthy or unhealthy) beverage a consumer has had during the day. Two, it accounts for anticipatory responses (forward looking) to health effects of future consumption and anticipated future health effects of current consumption. Accumulated consumption of unhealthy drinks can be detrimental to consumers' long-term health. However, it is normally not easy for people to monitor small changes in their health status. Hence, trying to regulate the daily total intake of unhealthy drinks can serve as a practical rule of thumb or heuristic to help consumers achieve their long-term health and nutrition goals. We therefore model the consumer as having a negative utility if the consumer falls short or exceeds a target number of unhealthy drinks for the day respectively. Hence if the consumer anticipates later situations where he is likely to drink an unhealthy drink, he is more likely to drink a healthy drink earlier in the day.

We accommodate three types of heterogeneity in self-regulating behavior: impulsive (myopic), adaptive (backward-looking), and anticipatory (forward-looking). Each consumer is of one of the three types. Consumers' types are constant over time. Since there is 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, and model the data as a mixture of the three types of consumers (see e.g., Kamakura and Russell 1989).[13]

[13] 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, Silverman and Sloan (2007), Chevalier and Goolsbee (2009), and Chung, Steenburgh and Sudhir (2011) for approaches to estimate discount factors when analyzing inter-temporal decision-making and forward looking behavior. The most general formulation would treat forward-looking ability as endogenous human capital (Becker and Mulligan 1997) but to our knowledge given the difficulty involved in doing this there is no empirical implementation of such a framework.

We model consumption at one of $t = 1,...,T$ periods in the day. Our modeling choices reflect the data we have at hand. 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 $c_{it} \in \{0,1,2,...,J\}$ denote a consumer i's choice of beverage j in period t out of a set of mutually exclusive beverage categories $\{0,1,2,...,J\}$, where 0 denotes the outside option of drinking nothing. Although, there are many attributes that may characterize a beverage based on our data we treat each beverage j as being characterized by four binary attributes,[14] i.e., (i) healthy—for notational convenience denoted as good (g_j), (ii) unhealthy—for notational convenience denoted as bad (b_j), (iii) mood boosting (m_j) and (iii) hydrating (h_j), where $g_j, b_j, m_j, h_j \in \{0,1\}$ (see Table 1). We define the values of the four attributes to be zero for the outside option. The sequence of choices made by an individual i over T periods in a day is denoted by $c_i \equiv (c_{it})_{t=1}^{T}$.

Empirically, we allow for J=6 beverage category choices and an outside option of drinking nothing in each time period t. As stated previously, each beverage is defined by 4 discrete attributes: healthy, unhealthy, mood boosting, hydrating. The 6 categories and the beverages included in each category are as follows (see Tables 1 and 2): (1) "Healthy" drinks – milk, juice, fruit smoothie, nutritional drink, (2) "Unhealthy" drinks – coffee, hot chocolate, powder soft drinks, soda, (3) "Mood" boosting drinks – milk shake, (4) "Hydrating" drinks – sports drinks, tap water, bottled water, (5) "Unhealthy & Mood" drinks – beer, wine, alcohol, frozen slush and (6) "Neutral" drinks – tea, energy drink. In addition to choosing a beverage from one of these 6 categories an individual at time t may also choose the outside option of drinking nothing. Hence, in each time period there are 7 choices available to the individual.

[14] See Chan (2006) for an alternative way to model attributes of beverages. The procedure works very well in his setting of carbonated soft drinks. A similar procedure is not feasible in our setting of multiple categories of beverages (e.g., carbonated soft drinks, tea, coffee, milk etc.) as it would expand the state space tremendously and make the model computationally intractable.

As defined g_{ijt}, b_{ijt} and m_{ijt} are respectively the healthy, unhealthy and mood boosting attribute of consumer i's choice j in period t respectively.[15] Define the accumulated stocks of these attributes to be, $G_{it} \equiv \Sigma_{s=1}^{t} g_{ijs}, B_{it} \equiv \Sigma_{s=1}^{t} b_{ijs}$, and $M_{it} \equiv \Sigma_{s=1}^{t} m_{ijs}$ for the healthy, unhealthy and mood boosting attributes respectively. The stocks represent how many drinks of a particular type, say healthy or unhealthy an individual has had so far that day. We allow for the current choice to depend on the accumulated stock of these attributes at period $t-1$. The dependence of a consumer's preference on $(G_{i,t-1}, B_{i,t-1}, M_{i,t-1})$ can either be the result of variety seeking behavior or inertia in tastes. Hence, we model habit persistence in consumption choices through product characteristics as opposed to by one-period lag-values of product choices.

We denote the activity that consumer i engages 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 activities: (1) eat, (2) work, (3) watch TV, (4) relax, (5) party or (6) exercise (see Table 3). We assume that a_{it} follows a first order Markov Process. The transition takes the nonparametric form, i.e., the conditional mass for each 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 would be specified as $\widehat{\Pr}[a_t \mid a_{t-1}, t]$ where a_t and $a_{t-1} \in \{1,2,3,4,5,6\}$.

Conditional on the activity, the consumer experiences a psychological or physical need state that enhances the utility from beverage consumption. These contemporaneous need states may be one of three kinds: health $(E_{it,1})$, mood $(E_{it,2})$ and hydration $(E_{it,3})$. 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 the lunch break an individual's needs may be best met by a bottle of water as the person is high on the health and

[15] As a mnemonic, the notation g (good) relates to healthy, and b (bad) relates to unhealthy. We prefer the healthy/unhealthy classification for better interpretation of our model and results.

hydration need, 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. We model these needs to be associated with each period's activity in the following way,

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

where $\delta_k(a_{it})$ are activity specific constants, and $\eta_{it,k}$ are normal random variables. We define $E_{it} \equiv (E_{it,1}, E_{it,2}, E_{it,3})$. These need states summarize the psychological and physical needs accompanying the various activities. We construct these three need states E_{it} using factor analysis on stated consumer data from 18 questions (see Section 2) about the psychological and physical needs that motivated the consumption decision in each period. The three need states are the three factors which explained the most variation in the individual responses to the 18 possible reasons in the survey that could have motivated consumption at a given occasion.

One of the contemporaneous factors that will affect consumption of a beverage in the short run will be 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 a given period. We model the evolution of the thirst stock to be endogenously determined as in stockpiling models (see e.g., Erdem, Imai and Keane 2003, Hendel and Nevo 2006) as follows:

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

Let $B_{iT} = \Sigma_{t=1}^{T} b_{it}$ denote the sum of unhealthy attributes of all 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 entire sample range in our data.

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

3.1 Anticipatory Self-Regulation: Forward Looking Behavior

We begin by describing the forward looking type—the most general form of self-regulatory behavior. This type consume beverages in response to (1) contemporaneous need state and thirst stock; (2) past consumption and (3) future anticipated consumption. We describe the preferences of these consumers through the following utility function:

$$V_{jt} = U_{jt} + \varepsilon_{jt} \ ,$$

where, U_{jt}, is the deterministic component of the utility function and is specified as follows,

$$\begin{aligned} U_{jt} = \alpha_0 + g_j(&\alpha_{10} + \alpha_{11}E_{t,1} + \alpha_{12}E_{t,2} + \alpha_{13}E_{t,3} + \alpha_{14}G_{\max} + \alpha_{15}B_{\max} + \alpha_{16}g_{t-1}) + \\ & b_j(\alpha_{20} + \alpha_{21}E_{t,1} + \alpha_{22}E_{t,2} + \alpha_{23}E_{t,3} + \alpha_{24}G_{\max} + \alpha_{25}B_{\max} + \alpha_{26}b_{t-1}) + \\ & m_j(\alpha_{30} + \alpha_{31}E_{t,1} + \alpha_{32}E_{t,2} + \alpha_{33}E_{t,3} + \alpha_{34}G_{\max} + \alpha_{35}B_{\max} + \alpha_{36}m_{t-1}) + \\ & h_j(\alpha_{40} + \alpha_{41}E_{t,1} + \alpha_{42}E_{t,2} + \alpha_{43}E_{t,3} + \alpha_{44}G_{\max} + \alpha_{45}B_{\max}) + \\ & Q_t \cdot 1\{j \neq 0\}(\beta_1 + \beta_2 G_{\max} + \beta_3 B_{\max}), \end{aligned} \tag{3}$$

and ε_{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, b_j, m_j, h_j) and the need states $(E_{t,1}, E_{t,2}, E_{t,3})$ capture the match values of the beverage attributes for the current need states (which are a function of activity and social environment). For example, a mood enhancing drink, such as beer, might have a high match value for parties. The thirst stock term, Q_t, captures the need to quench thirst, when a consumer has not drunk anything for Q_t consecutive periods. The utility function also includes the attributes of the choice made in the previous period, i.e., $(g_{t-1}, b_{t-1}, m_{t-1}, h_{t-1})$. This term helps capture the effect of past choices on current consumption. The interaction term $\alpha_{16} g_j g_{t-1}$, for example, captures the impact of drinking something with the healthy attribute in the previous period on the current period's preference for it. The coefficient of the interaction terms can be either positive or negative. 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. In contrast our model uses information about actual consumption decisions and short run 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 discuss the interpretation of the coefficients in the utility function. The parameters $(\alpha_{10}, \alpha_{20}, \alpha_{30}, \alpha_{40})$ represent the base level of utility from the healthy, unhealthy, mood-boosting and hydrating attributes respectively of the beverage chosen by the consumer. The total utility from an attribute also depends on the interaction of the attribute with the contemporaneous need states. This interaction reflects how the beverage matches the need states. The parameters $(\alpha_{11}, \alpha_{21}, \alpha_{31}, \alpha_{41})$ represent the utility of the four attributes for the chosen beverage 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 for the chosen beverage interacted with the level of mood need $(E_{t,2})$. The parameters $(\alpha_{13}, \alpha_{23}, \alpha_{33}, \alpha_{43})$ represent the utility of the four attributes for the chosen beverage interacted with the level of hydration need $(E_{t,3})$.

The parameters $(\alpha_{14}, \alpha_{24}, \alpha_{34}, \alpha_{44})$ and $(\alpha_{15}, \alpha_{25}, \alpha_{35}, \alpha_{45})$ account for the fact that some people simply drink more frequently than others. These parameters represent the utility from each of the four attributes (g_j, b_j, m_j, h_j) interacted with the (maximum) daily frequency of consumption of healthy and unhealthy attributes respectively, i.e., $G_{i,\max} = \max G_{iT}$ and $B_{i,\max} = \max B_{iT}$. 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 while the second and third parameters reflect the effect of thirst accounting for the heterogeneity in frequency of beverage consumption as described above. The parameters $(\alpha_{16}, \alpha_{26}, \alpha_{36})$ allow for self-regulation of current consumption in response to past consumption. Depending on their signs these parameters may capture either consumption persistence or variety seeking for the healthy, unhealthy and mood-boosting attributes. We do not incorporate such persistence for the hydration attribute as 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 believe that an end-of-day salvage value function based on the current day's overall consumption (that we describe below) can be 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 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). Therefore 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,

$$\bar{V}_{T+1}(B_T) = \delta_1(B_T - B_{\max}) + \delta_2(B_T - B_{\max})^2 \ , \tag{4}$$

where $B_{i,T}$ 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 $B_{i,\max}$ as the benchmark to capture such heterogeneity in consumers' "rule-of-thumb" with regard to staying healthy. The salvage value function contains the parameters (δ_1, δ_2). The first parameter (δ_1) accounts for the utility if the end of day consumption of the unhealthy attribute is less than the individual's threshold of daily amount of the unhealthy attribute. The second parameter (δ_2) accounts for the utility from the square of the (same) deviation, i.e., for utility from any deviation above or below the threshold. Thus, the first parameter accounts for linear effects while the second accounts for any non-linear effects (in the spirit of convex costs) of end of day cumulative consumption.

3.1.2 Value Function for Anticipatory Self-Regulators

A forward-looking consumer's 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 the future effects of current choices. So we model a forward-looking consumer's preference by the following value function:

$$\begin{aligned} V_{jt}(Q_t, G_{t-1}, B_{t-1}, M_{t-1}) &= U_{jt} + \beta V_{t+1}(Q_{t+1}, G_t, B_t, M_t) + \varepsilon_{jt} \\ s.t.\ Q_{t+1} &= 1\{j=0\} \cdot (Q_t + 1) \\ G_t &= G_{t-1} + g_j, B_t = B_{t-1} + b_j \\ M_t &= M_{t-1} + m_j \ , \end{aligned} \tag{5}$$

where β is the inter-temporal discount factor and V_{t+1} is the continuation value defined recursively as follows,

$$V_{t+1}(Q_{t+1}, G_t, B_t, M_t) = E(\max_j \{V_{j,t+1}(Q_{t+1}, G_t, B_t, M_t)\}), \qquad \text{if } t < T \tag{6}$$

with the expectation taken over the joint distribution of $(\varepsilon_{jt})_{j=1}^{J}$, and,

$$V_{t+1}(Q_{t+1}, G_t, B_t, M_t) = \bar{V}_{T+1}(B_T), \qquad \text{if } t = T \tag{7}$$

Lastly, a forward-looking consumer makes a choice to maximize the value each period, that is

$$c_t = \underset{j \in \{0,1,2,..,J\}}{\arg\max} \{V_{jt}\}$$

Given that our frequency of decision making is two hours and the entire horizon of decision making is a day, we assume the inter-temporal discount factor (β) across periods within a day to be one.

3.2 Adaptive Self-Regulators: Backward Looking Behavior

We define adaptive consumers as those who respond not only to their contemporaneous needs but also respond adaptively 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 can be described by the following utility function:

$$V_{jt} = U_{jt} + \varepsilon_{jt} \ ,$$

where, U_{jt}, is the deterministic component of the utility function specified above in Equation 3. Further, their utility function excludes end-of-day salvage value function (Equation 4). The backward-looking consumers make a choice to maximize their utility every period, that is

$$c_t = \underset{j \in \{0,1,2,..,J\}}{\arg\max} \{V_{jt}\}$$

3.3 No Self-Regulation ("Impulsive"): Myopic Behavior

We define impulsive consumers as those who consume beverages in response solely to contemporaneous need states and the thirst stock. These consumers are impulsive in as much as they ignore the effects of their past or future choices. For these consumers, we assume that their preferences are captured by the following utility function

$$V_{jt} = U_{jt} + \varepsilon_{jt} \ ,$$

where U_{jt} is the deterministic component of utility and is specified as follows,

$$\begin{aligned} U_{jt} = \alpha_0 &+ g_j(\alpha_{10} + \alpha_{11}E_{t,1} + \alpha_{12}E_{t,2} + \alpha_{13}E_{t,3} + \alpha_{14}G_{\max} + \alpha_{15}B_{\max}) + \\ &b_j(\alpha_{20} + \alpha_{21}E_{t,1} + \alpha_{22}E_{t,2} + \alpha_{23}E_{t,3} + \alpha_{24}G_{\max} + \alpha_{25}B_{\max}) + \\ &m_j(\alpha_{30} + \alpha_{31}E_{t,1} + \alpha_{32}E_{t,2} + \alpha_{33}E_{t,3} + \alpha_{34}G_{\max} + \alpha_{35}B_{\max}) + \\ &h_j(\alpha_{40} + \alpha_{41}E_{t,1} + \alpha_{42}E_{t,2} + \alpha_{43}E_{t,3} + \alpha_{44}G_{\max} + \alpha_{45}B_{\max}) + \\ &Q_t \cdot 1\{j \neq 0\}(\beta_1 + \beta_2 G_{\max} + \beta_3 B_{\max}) \ . \end{aligned}$$

The utility function of the impulsive consumers differs from that of the backward-looking types because it excludes the attributes of the choice made in the previous period, i.e., $(g_{t-1}, b_{t-1}, m_{t-1}, h_{t-1})$. It differs from that of the forward-looking type because it excludes the end-of-day salvage value function. Hence, these types are the most limited in their ability to self-regulate consumption. Then impulsive consumers make a choice to maximize their utility every period, that is

$$c_t = \underset{j \in \{0,1,2,..,J\}}{\arg\max}\{V_{jt}\}$$

To close the model, we assume that each consumer belongs to one of the three types of self-regulatory behavior. Let p_{i1}, p_{i2} and p_{i3} denote the probability that a consumer i belongs to the impulsive, 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

In this section we describe our procedure to estimate the model parameters including the shares of the three types of consumers. We first estimate the activity transition matrix non-parametrically. Next, we estimate the needs-activity regressions specified in Equation (1). With these estimates in hand we estimated the utility parameters of the structural model.[16]

[16] 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. We test for the empirical plausibility of this assumption later.

Denote the parameters describing the primitives in the utility functions of the three types of consumers as γ_1, γ_2, and γ_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, ε_{jt}, are i.i.d 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 impulsive and backward-looking consumers, we can easily compute their conditional choice probabilities respectively as,

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

and

$$\Pr(c_{it} = j \mid Q_{it}, E_{it}, G_{i,t-1}, B_{i,t-1}, M_{i,t-1}; \gamma_2) = \frac{\exp(U_{jt}(Q_{it}, E_{it}, G_{i,t-1}, B_{i,t-1}, M_{i,t-1}; \gamma_2))}{1 + \Sigma_{j'} \exp(U_{j't}(Q_{it}, E_{it}, G_{i,t-1}, B_{i,t-1}, M_{i,t-1}; \gamma_2))}$$

For the anticipatory consumers, we can recursively compute the expected continuation value functions, V_{t+1}, starting from the last period using Equations (5), (6), and (7) (see e.g., Rust 1987, 1994, Aguirregabiria and Mira 2010).[17] Then the model predicted conditional choice probabilities have the following logit functional form:

$$\Pr(c_{it} = j \mid Q_{it}, E_{it}, G_{i,t-1}, B_{i,t-1}, M_{i,t-1}; \gamma_3) = \frac{\exp(V_{jt} - \varepsilon_{jt})}{1 + \Sigma_{j'} \exp(V_{j't} - \varepsilon_{j't})}$$

We will suppress the dependence on the state variables for the conditional choice probabilities in the following to simplify the notation. One way to proceed is to estimate the structural parameters and the type shares is by using brute force Full Information Maximum Likelihood

[17] We solve the optimal choice function for the forward-looking model by using backward induction. The continuation value function in the last period is just the end-of-day scrap value function. The choice specific utility in the last period is simply the choice specific per-period utility plus the choice specific continuation value, and thus the optimal choice probabilities can be computed easily for the last period. For earlier periods, we first recursively solve for the expected continuation values, and then compute the optimal choice probabilities similarly.

Estimation (FIML) method in a "single" step. The unconditional likelihood of observing a sequence of choices for a consumer can be expressed as follows:

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

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

$$(\gamma^*, p^*) = \underset{(\gamma,p)}{\arg\max} \sum\nolimits_{i=1}^{N} \ln(L(\gamma \mid c_i))$$

The above problem is difficult to solve, because the optimization is taken over the space of all the parameters (74 parameters in our case), and the objective function is highly nonlinear in the parameters.

Alternatively, we can use the EM-algorithm to compute the MLE estimates, which would greatly reduce the computational difficulty. The intuition of EM-algorithm can be made transparent through the following basic equivalence result, stated in terms of our application. The MLE estimate is given by

$$(\gamma^*, p^*) = \underset{(\gamma,p)}{\arg\max}\, E_{c_i \mid \gamma^*, p^*}\left(\ln(\Sigma_{k=1}^{3} p_k \Pr(c_i \mid \gamma_k)) \right) ,$$

which can also be computed the following way,

$$(\gamma^*, p^*) = \underset{(\gamma,p)}{\arg\max}\, E_{c_i, k \mid \gamma^*, p^*}\left(\ln(p_k \Pr(c_i \mid \gamma_k)) \right) \quad .$$

It is to be noted that,

$$\begin{aligned}
&E_{c_i, k \mid \gamma^*, p^*}(\ln(p_\kappa \Pr(c_i \mid \gamma_k))) \\
&= E_{c_i \mid \gamma^*, p^*} E_{k \mid c_i, \gamma^*, p^*}(\ln(p_k \Pr(c_i \mid \gamma_k))) \\
&= E_{c_i \mid \gamma^*, p^*} \Sigma_\kappa \Pr(\kappa = k \mid c_i; \gamma^*, p^*)(\ln(p_\kappa \Pr(c_i \mid \gamma_\kappa))) \\
&= \Sigma_\kappa E_{c_i \mid \gamma^*, p^*} \Pr(\kappa = k \mid c_i; \gamma^*, p^*)(\ln(p_\kappa \Pr(c_i \mid \gamma_\kappa))) \quad .
\end{aligned}$$

Thus we have that,

$$(p_k^*, \gamma_k^*) = \underset{\gamma_k}{\arg\max}\, E_{c_i \mid \gamma^*, p^*} \Pr(\kappa = k \mid c_i; \gamma^*, p^*)(\ln p_\kappa \Pr(c_i \mid \gamma_\kappa))), \tag{8}$$

which suggests that, given (γ^*, p^*), we can compute (p_k^*, γ_k^*) by solving the above much simpler optimization problem that involves only the conditional choice probabilities for type k. The basic idea of EM algorithm is to replace the (p_k^*, γ_k^*), which is unknown, in the conditional expectation in Equation (8) with some initial guess, and compute the first step estimates. Then one can iterate the procedure by replacing (p_k^*, γ_k^*) with new estimates until the estimates converge.

Formally, we can use the following algorithm to compute the MLE estimates. Let $\theta \equiv (\gamma, p)$, and let θ^* denote the MLE estimate of θ and $\theta^{(1)}$ be the initial guess of θ^*. Furthermore, let $L(\theta^{(n)} \mid c_i) = \sum_{k=1}^{3} p_k^{(n)} \Pr(c_i \mid \gamma_k^{(n)})$ denote the unconditional likelihood of observing the consumption sequence of consumer i, and $p_{ik}^{(1)} = \dfrac{p_k^{(1)} \Pr(c_i \mid \gamma_k^{(1)})}{L(\theta^{(1)} \mid c_i)}$ denote the initial guess of the posterior probability of consumer i being of type k. Then we can update our estimate of the parameters using the following recursive formula:

$$
\begin{aligned}
\gamma_k^{(2)} &= \arg\max_{\gamma'_k} \sum_{i=1}^{N} p_{ik}^{(1)} \log(\Pr(c_i \mid \gamma'_k) \\
p_k^{(2)} &= \sum_{i=1}^{N} p_{ik}^{(1)} / N \\
p_{ik}^{(2)} &= \frac{p_k^{(2)} \Pr(c_i \mid \gamma_k^{(2)})}{L(\theta^{(2)} \mid c_i)}
\end{aligned}
$$

Similarly, we compute the updated estimate of $\theta^{(3)}$ based on $\theta^{(2)}$, and so on. In this way, we get a sequence of estimates, $\theta^{(1)}, \theta^{(2)}, \theta^{(3)}, ..., \theta^{(n)}$.

Dempster, Laird and Rubin (1977) show that

$$L(\theta^{(n+1)} \mid c_i) \geq L(\theta^{(n)} \mid c_i) \quad ,$$

and given that the Hessian of $\log(p_k \Pr(c_i \mid \gamma_k))$ is negative definite and has eigenvalues bounded away from zero, the sequence of estimates converges to the MLE estimate, that is $\theta^{(n)} \rightarrow \theta^*$. In the above algorithm, we are maximizing the simpler conditional log-likelihood over a smaller space of parameters of each consumer type. Computing the updates of the estimates given the previous estimates is much easier than to compute the MLE estimate in a single step. So we adopt the EM-algorithm to compute the MLE estimate of the structural parameters in our model.

We do not discuss identification in great detail as it relies on assumptions that are conventional in the literature. 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 impulsive type is independent of the previous choices, while that of the backward looking type is not. The choice probability of the adaptive type is independent of the number of periods left while that of the anticipatory type is not. We checked the validity of these implications after estimating the model (see footnote 18).

5 Results and Discussion

5.1 The Activity Transition Matrix

We report the activity transition matrix in Table 7 for each period. The activity matrices are intuitive once we take into account the different time periods. Period 1 is around breakfast; hence there is substantial transition into "work" during period 2. There is substantial transition into lunch in period 3—an "eating" activity. In the fourth period, most people transition back into work. In period 5, i.e., early evening, people transition into "dinner" or "TV." In period 6, late evening, individuals mostly transition into TV. After estimating the model we statistically tested and could not reject the null hypothesis of the homogeneity of the activity transition matrix across the different types of self-regulating individuals (see footnote 18).

5.2 Activity-Need Linkage Equations

Table 8 reports the results of Equation 1, the link between needs and activities. The health need is most strongly associated with eating and TV and least with party and work. We caution that lunch is classified as eating (even if one were at work), hence work includes only purely work times, when eating is not dominant. The mood need is most strongly associated with party, and least with eating. The hydrate need is most associated with exercise, and least associated with eating. All of the activity-need linkages have great face value. We treat the need functions in Equation (1) as homogeneous across the different (self-regulatory) types of consumers. As stated earlier for the activity transition matrix, after estimating the model we statistically tested and could not reject the null hypothesis of the homogeneity of these need regressions (see below).

5.3 Model Estimates

We begin by reporting the share of the three different types of self-regulators (p_1, p_2, p_3) in Table 9a. Most consumers are adaptive (45%), followed by the impulsive consumers (39%) and anticipatory consumers (17%). Thus, there is moderate ability to self-regulate in the population, with a significant portion of the population not having self-regulatory abilities at all. Only about a sixth of the population is fully self-regulatory in that they are both adaptive and anticipatory.[18]

In terms of the estimated parameters associated with the product attributes, we discuss the key takeaways (see Table 9b). First, only the unhealthy intercept is positive (and across all segments), consistent with the fact that the unhealthy drinks have the highest overall share.[19] Second, the attributes and the corresponding need interactions generally have face validity across all three segments. The health attribute-health need interaction is positive across all three segments. The unhealthy attribute interacts negatively with the health need state and hydration (a health neutral state), while it interacts positively with the mood need. The mood attribute positively interacts with the mood need (and has a much smaller positive interaction with the health need), but a strong negative interaction with hydration (the health neutral need).

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[18] We assessed how the three levels of self-regulation are identified from the data through a reduced form static logit choice model for current choice. For the fully self-regulatory anticipatory segment, both past consumption and future consumption impact current choice (the estimates are statistically significant). For the backward looking, adaptive segment, only past consumption impact current choice; while for the myopic, impulsive segment neither the past nor future is significant. These results give us confidence in the validity of the identified segments Also we tested whether we could reject the null of homogeneous activity transition matrices across the three segments based on the activity transition matrices computed based on individuals classified into the three segments.

[19] The common intercept and a number of other utility parameters are negative because consuming "nothing" is the outside good which has a relatively high share irrespective of activity and occasion (see Table 5). The model rationalizes this by estimating a relatively higher utility for the outside good for a high proportion of occasions.

In terms of capturing the heterogeneity associated with the general level of healthy and unhealthy drink consumption, the healthy attribute interacts positively with healthy drink consumption ($G_{\max}$) and the unhealthy attribute interacts positively with unhealthy drink consumption ($B_{\max}$). For state dependence captured through lagged consumption, we find that: (1) there is variety seeking for healthy products across both the adaptive and anticipatory segments; i.e., a healthy drink is more likely followed by an unhealthy drink, (2) there is inertia for mood products for both segments; a mood drink is more likely to be followed by a mood drink and, (3) there is variety seeking among the adaptive segment for bad drinks, who avoid a bad drink the next time after they have a bad drink, but state dependence for the anticipatory segment. However, such state dependence for bad drinks is balanced by these individuals through their forward looking behavior in that they have convex costs for exceeding their target level of bad drinks, and thus regulate their overall consumption of bad drinks.

Finally, we discuss the response to stock of thirst in terms of whether individuals consume a beverage (the "inside good"). From the estimates of the parameters $(\beta_1, \beta_2, \beta_3)$ we see that impulsive individuals respond to stock of thirst the least, while adaptive and anticipatory individual respond about the same. However, individuals who drink a lot (high $G_{\max}$ and $B_{\max}$), respond less to the stock of thirst across all three types, because they drink frequently independent of the stock of thirst.

5.4 Counterfactual Experiments

We perform three primary counter factual experiments.[20] The first two counterfactuals examine the impact of introduction of two new products. A feature of our model is that

[20] We conduct simulations for the benchmark and counterfactual environment in the following way. For each consumer, we first simulate the beverage consumptions under the three different self-regulatory decision modes in the benchmark case (i.e. with the original transition matrices and available product choices) over 4 weeks (20 weekdays in total). Then for each consumer, we simulate the consumption in the counterfactual environment (e.g. with the availability of the new product) or the probability of transitioning to party in last period changed to one) similarly for 20 days. We compute

individuals consume “bundles of attributes” as opposed to “market products” in a dynamic framework. Hence, it is natural in our setting to think about introducing a new product as a novel combination of attributes. (see e.g., Petrin 2002). We consider two products: one a healthy-hydration beverage high on the healthy and hydration attributes, and the second, mood-hydration beverage that is high on the mood boosting and hydration attributes.

As seen in the middle panel of Table 10 the health-hydration drink does extremely well. The product gains about 17% market share. This gain comes not only from cannibalizing the market share from other existing products but also expanding the category. The proportion of people not consuming anything decreases by 0.04 which is a category expansion of 6%. The share of healthy drinks drops by almost 50% and the drop in the share of the hydration drinks is almost of the same magnitude. The intuition is evident from Table 9b. The interaction terms of healthy attribute on hydrate (α_{13}) and the hydrate attribute on health (α_{41}) are either positive or relatively small negative values relative to all other interactions. Thus, the health-hydration product meets a latent unmet need that the products with only the healthy or hydration attributes in isolation are not able to provide.

Figure 3 shows the gain in market share for this new product conditional on activity. The biggest gain in market share is in the eating activity. Eating comprises the largest share among all activity states (more than 30%, see Table 3) and the health and hydration needs do have very high average consumption for this activity. Figure 4 reports the gain in market share of the health-hydrating product among the three types of self-regulators. One might conjecture that anticipatory regulators may be most receptive to this product, but it turns out that both in terms of conditional (on type) and unconditional share, the product is most favored by the impulsives. Indeed, the unconditional market share among the anticipatory individuals is only 19%, while the market share among the adaptive and impulsive types are much higher at 33% and 48%

the average consumption for a self-regulatory type in each case by taking the average of individual consumer's consumptions weighted by their probability of belonging to each type.

respectively, because of the greater market share of these segments overall. In our second counterfactual, reported in the bottom panel of Table 10, the mood-hydration product does not gain much traction in the market. The primary reason can be seen from Table 9b, where we can see that the interaction terms of mood attribute on hydrate (α_{33}) and the hydrate attribute on mood (α_{42}) are the most negative values relative to all other interactions for all segments. Simply put, when the hydration need is high a consumer doesn't really care much about a drink with a mood enhancing attribute, or when the mood need is high, does not care much about a drink with the hydrating attribute.[21]

Finally, we consider a counterfactual experiment motivated from a policy perspective about encouraging healthy food and beverage consumption, and the obesity epidemic. The problem of weight gain (and how one can control it), during the holiday season where one is constantly tempted by a larger than usual number of parties and dining occasions is the subject of widespread media and consumer interest. We consider how the three different types "self-regulators" are differentially affected by the "Holiday Effect." We operationalize the "Holiday Effect" by assuming that individuals are at a party at the end of the day with probability one. The results of the counterfactual are reported in Table 11 and summarized in Figure 5. Not surprisingly, we find that 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 during the holiday season. However, we find that the anticipatory individual deviates least from the baseline consumption; the impulsive individual deviates the most, with the adaptive individual falling in between. Thus self-regulatory nature should serve as an important segmentation variable from a policy perspective in communications strategies for combating obesity (see e.g., Schwartz et al. forthcoming).

[21] An example of a drink positioned as healthy-hydrating is "Honest Tea" with the tag line: "Nature got it right. We put it in a bottle." An example of mood-hydrating drink may is "SoBe" with its tag line, "Flavors with benefits." The name SoBe incidentally is inspired by the abbreviation for South Beach in Miami, FL; a location with a distinctive and glamorous life-style.

Figures 6a and 6b examine in greater detail the role of adaptive and anticipatory behavior in self-regulation. Figure 6a shows what happens to consumption of beverage categories for adaptive individuals if the effect of the lagged consumption choices is turned-off, i.e., parameters $(\alpha_{16}, \alpha_{26}, \alpha_{36})$ in Equation 3 are set to zero. Thus, if an adaptive individual behaved like an impulsive consumer, the consumption of unhealthy beverages increases. This increase is primarily at the expense of consuming "nothing" (the outside good), and secondarily from the neutral and hydration beverages. Thus, being adaptive in response to past consumption not only limits overall beverage consumption, but in particular reduces the consumption of unhealthy beverages.

Figure 6b examines the self-regulation effect of anticipatory behavior. We operationalize this by simulating beverage consumption when the scrap value function (Equation 4) is shut down, i.e., (δ_1, δ_2) are set to zero. Now the anticipatory individual becomes merely an adaptive individual. Due to the "adaptive" to "impulsive" switch, the outside good and pure hydration share goes down, while the consumption of both healthy and unhealthy beverages goes up. The consumption of neutral, hydrating, and unhealthy & mood-boosting beverages decreases. The reason both healthy and unhealthy beverage consumption goes up is due to variety seeking; with the fall in outside good share, unhealthy beverages are followed by healthy beverages and vice versa, leading to the increase in both types of consumption. Again the primary story is that anticipatory behavior helps limit overall consumption and the consumption of unhealthy beverages.

6 Conclusion

Most models of consumer choice in the literature are estimated using purchase data, but not actual consumption or usage. 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. In this paper, we introduce unique intra-day consumption, activity and needs data to understand 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. Therefore consumer choice needs to be modeled as a balance between short-run needs and long-term goals. We provide a dynamic structural framework that is amenable to modeling consumer self-regulation between short-run needs and long-term goals. Furthermore, health changes in response to consumption choices are manifested extremely gradually and are not easy for individuals to discern hence we implement long-term goals as heuristics or rules-of-thumb. The framework also enables modeling heterogeneity in the ability of consumers to self-regulate. Our modeling approach expands the existing dynamic structural modeling literature in allowing for consumption and stockpiling dynamics at the level of the product attributes (e.g., healthy, hydration etc.)

Our analysis provides insights on what kind of new product introductions are likely to be successful or unsuccessful. We find that health-hydration combination product will be successful, while mood-hydration combination is unlikely to be successful. Further, we are able to provide insight on how self-regulatory behavior helps consumers regulate unhealthy consumption, when faced with high short-run needs for unhealthy consumption. This has implications for policy makers tackling health and nutrition issues such as the obesity epidemic.

Finally, we now discuss limitations of our current work that provide opportunities for future research. Our research has focused on the beverages category, an important category in its own right, but it is important to assess whether the modeling framework we introduce can generalize to other consumption categories such as food. Further, 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 in order to obtain a "peak" experience. [22] In the current work, we do not have data on co-consumption, but modeling co-consumption leads to interesting modeling challenges and can help answer important substantive questions. For example, do consumers balance consumption within occasions or across time or both?

Our model was developed to explain steady state consumption behavior. 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 reached steady state. Such activities could include new recreational activities, where consumers seek to sample a range of activities, learn about one's tastes and abilities. One needs to expand the dynamic models to incorporate learning and yet model time allocation across activities in such situations.

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.

[22] There is a large volume of research on cross-category purchase behavior using scanner data (e.g., Manchanda et al. 1998; Niraj et al. 2008), but little on cross-category consumption. Levy et al. (2012) analyze the results of an intervention seeking to improve the purchases of healthier food and beverages but find no differential effects by race or job type (a proxy for socioeconomic status). See also e.g., Schwartz et al. forthcoming, for a field experiment based analysis of actual food consumption choices. Their study is based on data on food consumption choices by a cross-section of patrons at a Chinese fast-food restaurant. However, they found no evidence of this compensating or "licensing" behavior across different foods consumed on an occasion.

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Table 1: The Four Binary Attributes of Drinks

Drinks	Healthy	Unhealthy	Mood-boosting	Hydrating
coffee	0	1	0	0
tea	0	0	0	0
milk	1	0	0	0
hot chocolate	0	1	0	0
juice	1	0	0	0
sports drink	0	0	0	1
powder soft drink	0	1	0	0
soda	0	1	0	0
beer/wine/alcohol	0	1	1	0
water	0	0	0	1
bottled water	0	0	0	1
frozen slush	0	1	1	0
fruits smoothie	1	0	0	0
nutritional drink	1	0	0	0
energy drink	0	0	0	0
milk shake	0	0	1	0
other	0	0	0	0

Table 2: Drink Categories

Drink categories	Healthy	Unhealthy	Mood-boosting	Hydrating	Examples
1 (neutral)	0	0	0	0	tea
2 (healthy)	1	0	0	0	milk, juice
3 (unhealthy)	0	1	0	0	coffee, soda,
4 (mood-boosting)	0	0	1	0	milk shake
5 (hydrating)	0	0	0	1	sports drink, water
6 (unhealthy+mood)	0	1	1	0	beer, wine

Table 3: Categories of Occasions

Abbreviations	Occasions	Percent
Eat	Eat	31.6
Work	Deskwork, break from work, shopping, commute	24.5
TV	TV	21.3
Relax	Relax, house work, meeting, study	15.0
Party	Party, view shows, travel	5.7
Exercise	Exercise, physical activity	2.0

Table 4: Activity Shares by Time

Time	Activity					
	Eat	Work	TV	Relax	Party	Exercise
Breakfast	50.1	14.5	19.4	11.0	4.3	0.7
Morning	10.2	46.6	11.6	21.5	6.6	3.5
Lunch	52.8	23.6	10.7	8.9	3.2	0.7
Afternoon	6.5	41.4	17.1	22.4	8.1	4.4
Dinner	58.7	7.4	22.2	6.7	4.6	0.3
Evening	11.0	13.3	46.6	19.5	7.2	2.4

Table 5: Shares of Drink Categories by Activity

Activity	Drink Category					
	Nothing	Neutral	Healthy	Unhealthy	Mood	Hydrating	Unhealthy + Mood
Eat	33.1	6.9	19.9	25.5	0.3	12.4	1.9
Work	35.5	4.9	6.8	26.2	0.3	24.4	1.9
TV	43.5	5.0	10.7	21.8	0.2	16.0	2.8
Relax	42.7	4.9	9.3	19.4	0.2	20.4	3.0
Party	40.9	3.4	6.8	27.2	0.8	13.5	7.3

Table 6: Descriptive Statistics of Daily Consumption Activity

Variables	Obs.	25th Percentile	Median	75th Percentile	Mean	Std. Dev.	Min	Max
All categories	9400	3	4	5	3.7	1.2	0	6
Healthy drinks	9400	0	1	1	0.7	0.8	0	5
Unhealthy drinks	9400	1	1	2	1.6	1.2	0	6
Mood drinks	9400	0	0	0	0.2	0.4	0	3
Hydration drinks	9400	0	1	2	1.1	1.1	0	6
Other drinks	9400	0	0	0	0.3	0.6	0	5
Individual Level Maximum Daily Total Consumption								
Healthy drinks	2350	1	2	2	1.8	0.8	1	4
Unhealthy drinks	2350	2	3	4	3.1	1.1	1	5

Table 7: Activity Transition Matrices by Period

	Morning (t=2)					
Breakfast (t=1)	Eat	Work	TV	Relax	Party	Exercise
Eat	0.126	0.458	0.099	0.221	0.056	0.041
Work	0.073	0.632	0.059	0.161	0.051	0.023
TV	0.071	0.397	0.213	0.213	0.073	0.033
Relax	0.086	0.403	0.126	0.292	0.067	0.026
Party	0.107	0.473	0.052	0.159	0.187	0.022
Exercise	0.047	0.500	0.063	0.141	0.109	0.141
	Lunch (t=3)					
Morning (t=2)	Eat	Work	TV	Relax	Party	Exercise
Eat	0.592	0.185	0.086	0.098	0.031	0.007
Work	0.544	0.310	0.061	0.061	0.022	0.003
TV	0.440	0.122	0.295	0.110	0.030	0.002
Relax	0.513	0.192	0.108	0.145	0.034	0.009
Party	0.511	0.172	0.121	0.068	0.113	0.015
Exercise	0.550	0.182	0.134	0.076	0.024	0.033
	Afternoon (t=4)					
Lunch (t= 3)	Eat	Work	TV	Relax	Party	Exercise
Eat	0.079	0.429	0.146	0.227	0.077	0.041
Work	0.055	0.507	0.124	0.176	0.089	0.048
TV	0.041	0.249	0.391	0.220	0.062	0.039
Relax	0.044	0.315	0.192	0.346	0.058	0.045
Party	0.046	0.315	0.157	0.223	0.203	0.056
Exercise	0.016	0.443	0.098	0.148	0.164	0.131
	Dinner (t=5)					
Afternoon (t=4)	Eat	Work	TV	Relax	Party	Exercise
Eat	0.693	0.074	0.133	0.056	0.041	0.003
Work	0.600	0.085	0.207	0.062	0.043	0.003
TV	0.482	0.044	0.373	0.060	0.039	0.003
Relax	0.630	0.065	0.167	0.091	0.044	0.004
Party	0.555	0.097	0.209	0.048	0.088	0.003
Exercise	0.560	0.097	0.210	0.068	0.056	0.010
	Evening (t=6)					
Dinner (t=5)	Eat	Work	TV	Relax	Party	Exercise
Eat	0.134	0.117	0.451	0.206	0.068	0.024
Work	0.074	0.321	0.312	0.207	0.052	0.034
TV	0.069	0.107	0.609	0.135	0.062	0.017
Relax	0.099	0.132	0.396	0.282	0.069	0.022
Party	0.080	0.163	0.337	0.195	0.193	0.032
Exercise	0.032	0.129	0.226	0.323	0.129	0.161

Table 8: Regressions of Needs on Activity Dummies

Activity Dummies	Dependent Variable		
	Health Need	Mood Need	Hydrate Need
Eat	**1.145**	0.633	0.525
	(0.003)***	(0.003)***	(0.003)***
Work	0.700	0.919	1.084
	(0.004)***	(0.004)***	(0.004)***
TV	0.951	0.843	0.859
	(0.004)***	(0.004)***	(0.004)***
Relax	0.760	0.911	1.115
	(0.004)***	(0.005)***	(0.004)***
Party	0.712	**1.347**	1.086
	(0.007)***	**(0.007)*****	(0.007)***
Exercise	0.782	0.896	**2.201**
	(0.012)***	(0.013)***	**(0.012)*****
Observations	221592	221592	221592
R-squared	0.54	0.50	0.57

Standard errors in parentheses, ***: p<0.01, **: p<0.05, *: p<0.1

Table 9a: Model Estimates, Type Distribution

Consumer Types	Probability Mass	Std.dev
Impulsive	0.39	0.02
Adaptive	0.45	0.02
Anticipatory	0.17	0.01

***: p<0.01, **: p<0.05, *: p<0.1

Table 9b: Model Estimates, Type Specific Models

Parameters		Impulsive Type		Adaptive Type		Anticipatory Type	
		Coef.	Std.dev	Coef.	Std.dev	Coef.	Std.dev
Intercept (α_0)		-2.32***	0.03	-1.67***	0.02	-2.45***	0.04
Healthy attribute: intercept (α_{10})		-2.28***	0.13	-2.61***	0.12	-1.17***	0.22
	x health need (α_{11})	1.52***	0.03	1.50***	0.03	1.01***	0.04
	x mood need (α_{12})	-0.93***	0.04	-0.67***	0.03	-0.29***	0.04
	x hydrate need (α_{13})	-0.26***	0.03	-0.44***	0.03	-0.46***	0.04
	x G_{max} (α_{14})	0.95***	0.03	0.68***	0.03	0.91***	0.05
	x B_{max} (α_{15})	0.03	0.03	0.17***	0.02	0.11***	0.04
	x lagged healthy (α_{16})			-0.23***	0.05	-0.56***	0.09
Unhealthy attribute: intercept (α_{20})		0.47***	0.09	0.56***	0.08	0.51***	0.15
	x health need (α_{21})	-0.78***	0.03	-1.05***	0.03	-0.77***	0.03
	x mood need (α_{22})	0.57***	0.02	0.99***	0.02	0.38***	0.02
	x hydrate need (α_{23})	-0.78***	0.02	-1.51***	0.03	-0.59***	0.03
	x G_{max} (α_{24})	0.10***	0.02	0.09***	0.02	0.19***	0.04
	x B_{max} (α_{25})	0.45***	0.02	0.69***	0.02	0.53***	0.03
	x lagged unhealthy (α_{26})			-0.39***	0.03	0.21***	0.04
Mood attribute: intercept (α_{30})		-2.71***	0.21	-3.81***	0.22	-2.16***	0.37
	x health need (α_{31})	0.31***	0.06	-0.31***	0.06	0.09	0.10
	x mood need (α_{32})	1.05***	0.04	0.98***	0.04	0.62***	0.05
	x hydrate need (α_{33})	-1.26***	0.09	-1.59***	0.08	-1.20***	0.13
	x G_{max} (α_{34})	0.20***	0.06	-0.25***	0.04	0.02	0.08
	x B_{max} (α_{35})	-0.30***	0.04	0.08**	0.04	-0.35***	0.07
	x lagged mood (α_{36})			1.34***	0.13	0.72***	0.17
Hydrate attribute: intercept (α_{40})		4.26***	0.10	-1.59***	0.11	0.85***	0.10
	x health need (α_{41})	-0.35***	0.04	-0.32***	0.03	0.17***	0.03
	x mood need (α_{42})	-3.97***	0.08	-2.22***	0.04	-0.33***	0.03
	x hydrate need (α_{43})	0.91***	0.03	1.56***	0.03	0.60***	0.02
	x G_{max} (α_{44})	-0.57***	0.03	0.47***	0.02	0.35***	0.03
	x B_{max} (α_{45})	-0.19***	0.08	0.38***	0.02	-0.21***	0.02
Thirst stock:	intercept (β_1)	0.17**	0.08	0.59***	0.08	0.55***	0.11
	x G_{max} (β_2)	0.04*	0.03	-0.14***	0.02	-0.07**	0.04
	x B_{max} (β_3)	-0.03*	0.02	-0.10***	0.02	-0.11***	0.03
Salvage value:	linear term (δ_1)					-1.16***	0.07
	quadratic term (δ_2)					-0.04*	0.03

***: $p<0.01$, **: $p<0.05$, *: $p<0.1$

Table 10: Counterfactual Experiments 1 & 2: Introducing New Beverages

	Market share of beverage categories							
	Nothing	Neutral	Healthy	Unhealthy	Mood	Hydration	Unhealthy +Mood	New product
	Baseline							
Market share	0.38	0.05	0.11	0.25	0.00	0.18	0.02	
	Experiment 1: Introducing a new healthy/hydrating beverage							
Market shares	0.34	0.04	0.07	0.24	0.00	0.12	0.02	0.17
Share changes	-0.04	-0.01	-0.04	-0.02	0	-0.06	0	0.17
	Experiment 2: Introducing a new mood/hydrating beverage							
Market shares	0.38	0.05	0.11	0.25	0.00	0.18	0.02	0.01
Share changes	0	0	0	0.00	0	0.00	0	0.01

Table 11: Counterfactual Experiment: The "Holiday Effect"

	Total Accumulated Attributes			
Consumer types	Mood	Unhealthy	Healthy	Hydration
	Original			
Impulsive	3.6	27.5	14.3	25.1
Adaptive	1.9	37.2	11.9	21.4
Anticipatory	3.9	34.3	12.9	19.9
	Experiment 1: holiday effect, i.e. party every night (the last period)			
Impulsive	4.0	28.9	13.9	23.1
Adaptive	2.0	38.5	11.4	20.2
Anticipatory	4.1	35.5	12.8	19.2
	Percentage changes			
Impulsive	9.5	5.1	-3.3	-7.8
Adaptive	7.5	3.5	-4.7	-5.4
Anticipatory	4.2	3.2	-1.1	-3.2

Figure 1: Mean Needs by Activity

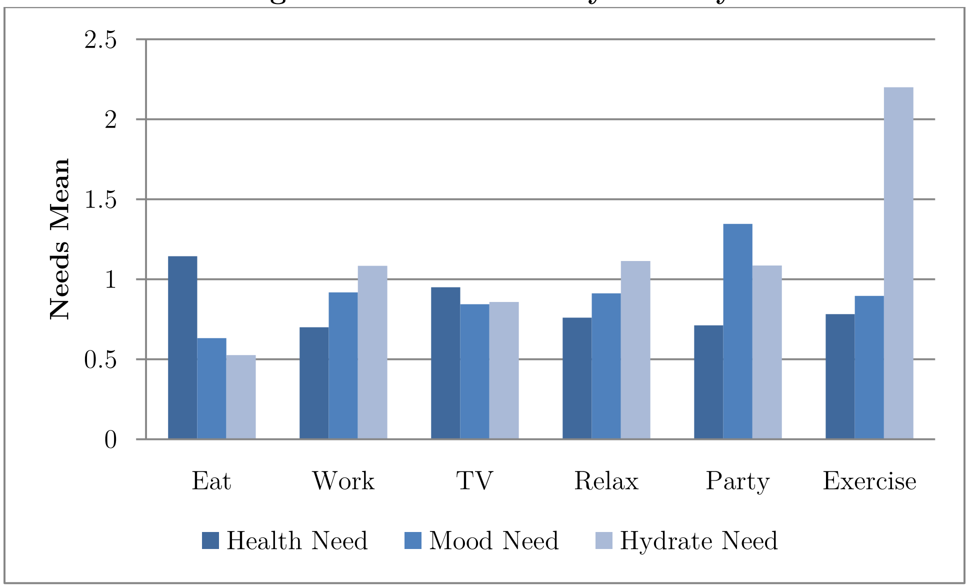

Figure 2: Introducing the Healthy & Hydrating Beverage: Gain in Market Share

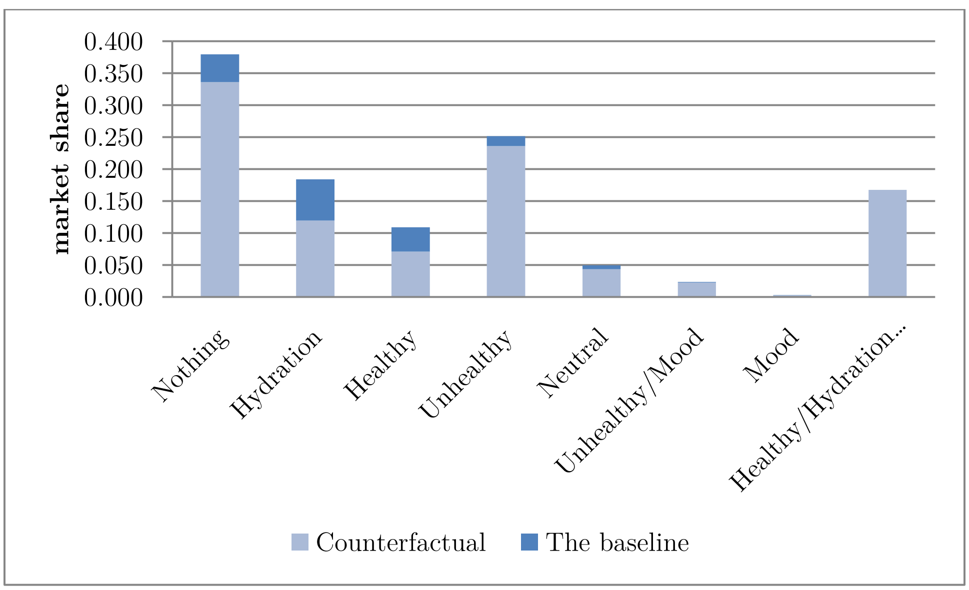

Figure 3: Introducing the Healthy & Hydrating Beverage: Market Shares by Activity

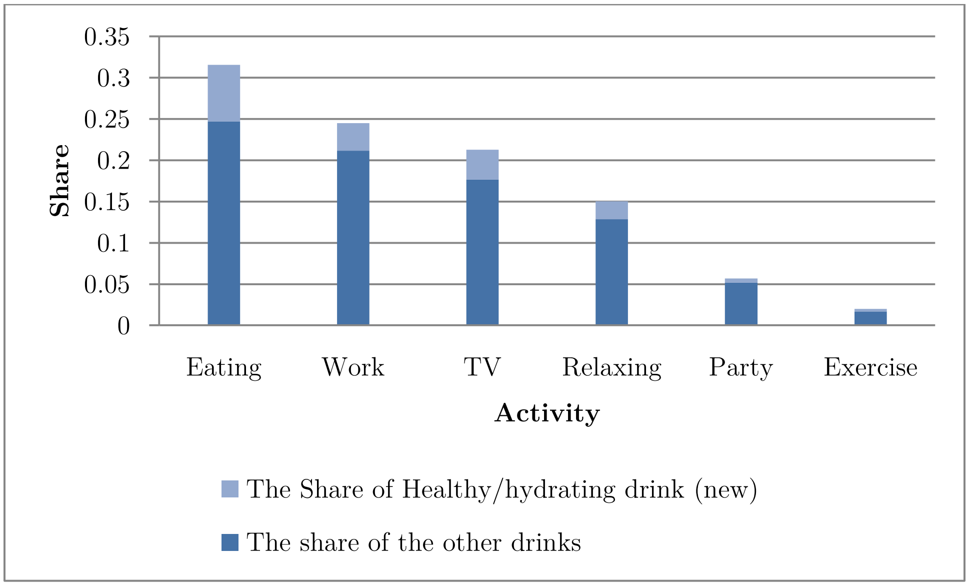

Figure 4: Introducing the Healthy & Hydrating Beverage: Market Share by Types

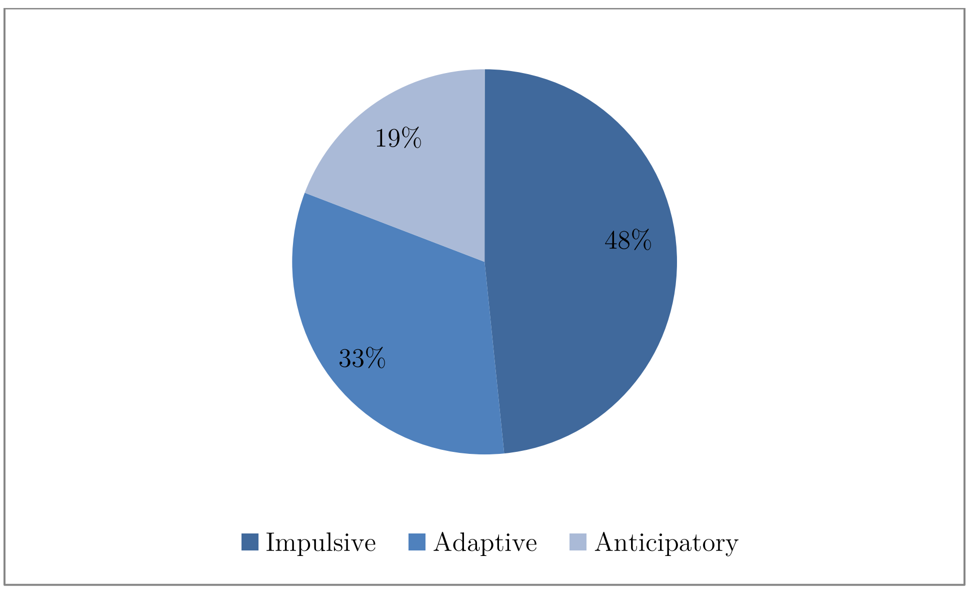

Figure 5: The “Holiday” Effect by Type

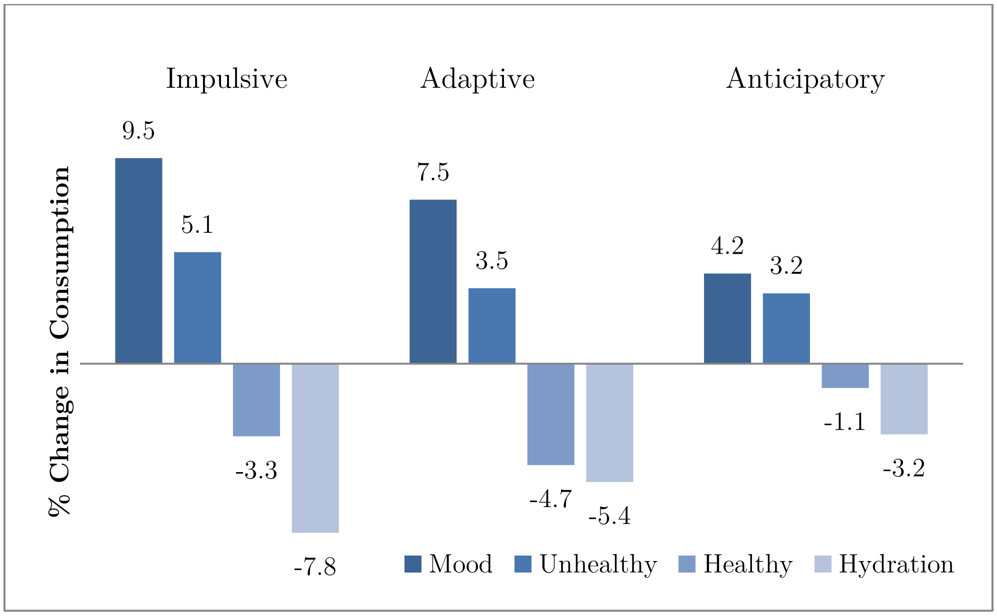

Figure 6a: The “Self-Regulation” Effect of Backward Looking Behavior

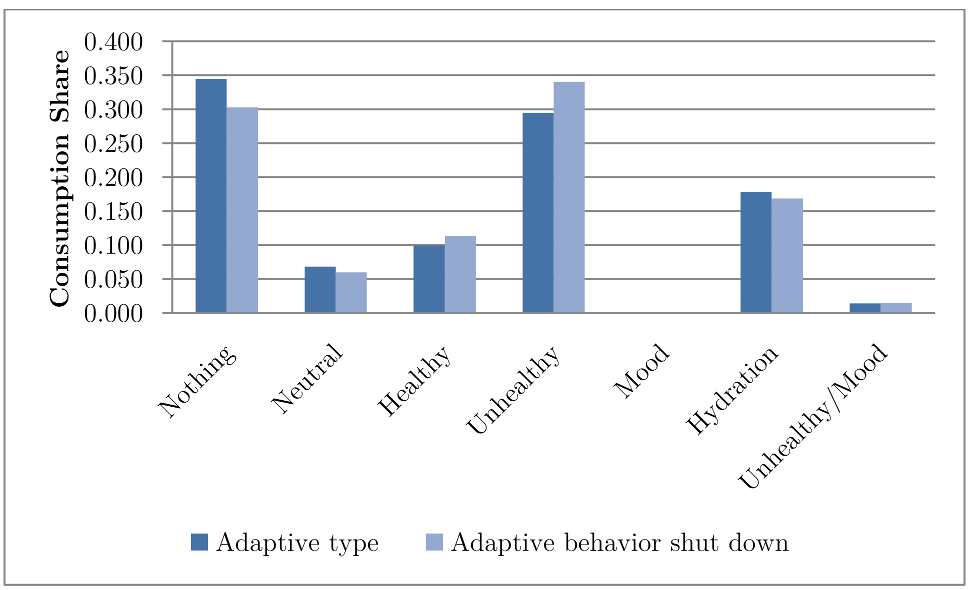

Figure 6b: The "Self-Regulation" Effect of Forward Looking Behavior