EMPIRICAL INVESTIGATION OF HABIT, VARIETY-SEEKING, AND SATIATION IN SNACK CONSUMPTION USING MULTIPLE DISCRETE-CONTINUOUS FRAMEWORK

by

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I dedicate this dissertation to my wife Sunisha and son Adithya Kamatham. I am greatly indebted to them for the support they provided through these five years. I dedicate this dissertation to my parents, Bhanumathi and Venkateswara Rao, and my sister Sr Lakshmi, who supported me through my formative years and guided me while I pursued my interests.

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by

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This dissertation consists of three research papers examining the role of satiation and state-dependence, choice sets, latent segments in the context of snack consumption. The three chapters specifically examine whether habituation or variety-seeking govern snacking.

In the second chapter, we explore variety seeking behavior in a richer context. By using the multiple discrete-continuous extreme value (MDCEV) framework we estimate a model that captures choice of multiple alternatives and quantity consumption. We investigate the effects of satiation and state dependence and use a rich panel data of individual snack consumption to estimate the model estimate the model. We use consumption data of individuals recorded through hand-held devices and model consumers' choices from a variety of snack categories. Using a single framework, we separate the effects of satiation, intrinsic utility, and state dependence. Our modeling approach provides evidence of greater variety seeking in consumers at a brand level than at the category level within a day across time-periods. Across days, we find that category consumption choices are driven by habituation. We find evidence of satiation or diminishing marginal utility, and that satiation varies by snack categories and by dayparts. We

show that by accounting for state-dependence and unobserved heterogeneity, the fit for MDCEV model improves tremendously over the base model that doesn't capture neither of these factors.
In the third chapter, we propose a new framework for modeling consideration sets in the MDCEV choice model framework. Using a gradient boosting algorithm from machine learning literature, we predict alternatives that are most likely to be chosen by a consumer at a daypart. In doing so, we reduce the computational burden associated with consideration set enumeration. These consideration sets are constructed as a function of dayparts, prior choices and prior choices, allowing us to predict alternatives that vary across individuals and time of the day. Our modeling approach allows us to estimate bias in parameter estimates, which is an outcome observed when choice models are estimated without inclusion of consideration sets. Using a rich panel data of individual level snack consumption, a setting where multiple discreteness and quantity choices play a role, along with groups of alternatives that are usually considered by individuals based on the time of consumption, we calibrate estimate the parameters of the model. We show that the proposed method provides a superior model fit by about 50% and reduces bias in parameter estimates compared to the base model. Using the proposed approach, we conduct two thought experiments – how does calorie consumption change when the time of consumption of a snack is changed and when a snack with switched with another snack.
In the fourth chapter, we uncover latent segments of consumers using their snack consumption behavior using the individual level snack consumption data. We estimate a model of choices and quantity consumption using the multiple discrete-continuous framework with latent segments. Our approach results in a three-segment structure for the snack consumers which are labeled as "old, overweight and inactive", "male and obese" and "young and active". Since our model

captures both preference for alternatives and quantity choices, we are able to get a better picture of consumption behavior. Latent segment models relied on the multinomial logit framework to uncover segments of consumers purely based on preferences alone. A fundamental assumption of is this model is that consumers face constant marginal utility. However, consumers do face diminishing marginal utility as we consume more of an alternative. Through the MDCEV framework, we relax this assumption and the models enables us to estimate a satiation parameter that captures diminishing marginal utility, thus giving us a complete picture of consumption behavior. To our knowledge, this is the first paper in marketing to show that satiation can also be used an additional dimension for customer segmentation apart from consumer preferences.
We find that category consumption is governed by habituation across days in just one of three segments. Within a day, the “male and obese” segment seeks more variety in category consumption over the other segments. We find that all three segments are brand variety-seekers within a day while habituated across days for brand choices. Preference levels for each category varies across segments, while satiation levels also differ across segments. We create profiles for the three segments and find that the calorie consumption varies significantly across the three segments varies by categories. Our results have implications for managers interested in creating optimal consumption bundles and for policymakers interested in addressing over-consumption leading to obesity among US consumers.

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CHAPTER 1

INTRODUCTION

In the second chapter, our goal is to use study variety seeking behavior in a richer context. We use the multiple discrete-continuous extreme value (MDCEV) framework to estimate a model that captures choice of multiple alternatives and quantity consumption. Using the context of snacking to capture variety seeking behavior, we propose a modified MDCEV model. We investigate the effects of satiation and state dependence and use a rich panel data of individual snack consumption to estimate the model. So far, prior models in the literature could not account for and separate intra-household heterogeneity from true variety seeking. By using consumption data of individuals recorded through hand-held devices we are able to model consumers' choices from a variety of snack categories. In a single framework, we separate the effects of satiation, intrinsic utility, and state dependence and control for the effect of covariates that affect each aspect. Our modeling approach provides evidence of greater variety seeking in consumers at a brand level than at the category level within a day across time-periods. We also find that consumers category consumption choices across days are driven by habituation. We find evidence of satiation or diminishing marginal utility, and that satiation varies by snack categories and by dayparts. Through this approach we show that the fit of MDCEV framework can be improved tremendously by including state dependence in the model. By estimating various specifications of the model, we show the improvement in model fit that can be achieved individually and together by including demographics, product characteristics and state dependence. We finally estimate a model that includes all of these characteristics and account for unobserved heterogeneity. We show that this model provides a better fit than the base model.

In the third chapter, I propose a new framework for modeling consideration sets in the MDCEV choice model framework. We integrate the MDCEV and the consideration sets literature in this chapter. In prior literature, models were constructed to study factors effecting consideration set formation in a two-stage choice model, using an enumeration methodology which is computationally infeasible with beyond ten choices. Instead, we propose a solution to reduce this complexity by using an ensemble method from the machine learning literature called XGBoost (extreme gradient boosting) algorithm. Using this algorithm, we predict the alternatives that a consumer is most likely to choose from, forming her consideration set. These consideration sets are constructed as a function of dayparts, prior choices and prior choices, allowing us to predict alternatives that vary across individuals and time of the day. Our modeling approach allows us to estimate bias in parameter estimates, which is known to happen when choice models are estimated without inclusion of consideration sets. We use a rich panel data of individual level snack consumption, a setting where multiple discreteness and quantity choices play a role, along with groups of alternatives that are usually considered by individuals based on the time of consumption. This setting allows us to estimate our model as the given number of alternatives are too large and individuals tend to choose from a smaller set of alternatives when snacking. We first estimate a benchmark model where individuals are assumed to choose from all alternatives. We then estimate a model with consideration sets generated by enumerating over the alternatives predicted the gradient boosting algorithm. We show that the proposed method provides a superior model fit by about 50% and reduces bias in parameter estimates compared to the base model. Using the proposed approach, we conduct two counterfactual experiments – changing time of consumption of a snack and switching a snack with another and estimate the change in calories consumed. The counterfactual experiments show that when a snack such as ice-cream is consumed in the afternoon instead of late night, the calorie consumption decreases by about 32%. Switching out snacks results in a decrease in calorie consumption by about 27%. We discuss implications for health policymakers and managers who are interested in implementing changes to snacks that could result in a decrease or increase in overall snack calorie consumption.

In the fourth chapter, we uncover latent segments of consumers who display homogenous snacking behavior using the individual level snack consumption data. Prior literature has shown that snacking accounts for about 25% of calories consumed in a day by US consumers. Consumers also make potentially over 200 food related choices in a day, and snacking being connected to obesity issues among US consumers. Given this, it is important for policymakers and marketers to understand what role various factors play in snack consumption choices. Using a rich panel data of snack consumption, we first estimate a latent class model of consumer preferences using choice data alone. We proceed to estimate a model of choices and quantity consumption using the multiple discrete-continuous framework. Our approach results in a three-segment structure for the snack consumers which are labeled as "old, overweight and inactive", "male and obese" and "young and active". Since our model captures both preference for alternatives and quantity choices, we are able to get a better picture of consumption behavior. Traditionally, latent segment models relied on the multinomial logit framework to uncover segments of consumers purely based on preferences alone. A fundamental assumption of is this model is that consumers face constant marginal utility. Whereas, in reality, we do face a diminishing marginal utility as we consume more of an alternative. Through the MDCEV framework, we relax this assumption and the models enables us to estimate a satiation parameter that captures diminishing marginal utility, thus giving us a complete picture of consumption behavior. To our knowledge, this is the first paper in marketing to show that satiation can also be used an additional dimension for customer segmentation apart from consumer preferences. We contribute to the literature in two ways: using quantity consumption, we demonstrate how satiation can be used as a new dimension for segmenting customers, and we provide a better understanding and description of the differences in preferences and quantity consumption among distinct population segments.

This model is estimated in a two-stage framework using the EM algorithm. In the first stage, we use a multinomial logit model to assign individuals to segment in a probabilistic manner. Given the segment membership, we use the multiple discrete-continuous extreme value (MDCEV) model to study the consumption choices. We estimate the latent class model with the MNL framework in a separate model. In both cases, we estimate a series of models with one to five latent segments. We find that the three-segment model provides a superior fit compared to all other models. In the MNL based framework, we describe the segments based on preferences alone. Whereas, in the MDCEV framework, we are able to describe segments based on both quantity (satiation) and preferences in a single model.

We find that category consumption is governed by habituation across days in just one of three segments. Within a day, the "male and obese" segment seeks more variety in category consumption over the other segments. We find that all three segments are brand variety-seekers within a day while habituated across days for brand choices. Preference levels for each category varies across segments. Satiation levels differ across segments – a unique feature of this model that allows us to understand quantity consumption along with preferences. Post segmentation, we create profiles for the three segments and find that the calorie consumption varies significantly across the three segments varies by categories. Consumers in these three segments differ in their satiation levels by time of day, and product characteristics. Our results have implications for managers interested in creating optimal consumption bundles and for policymakers interested in addressing over-consumption leading to obesity among US consumers.

CHAPTER 2

A NEW MODEL OF VARIETY SEEKING USING SNACK CONSUMPTION DATA: AN APPLICATION OF THE MULTIPLE DISCRETE-CONTINUOUS CHOICE MODEL

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Abstract

Recent developments in modeling both choice and quantity decisions with multiple category choices, notably the MDCEV models (Bhat 2005, 2008), permit one to study variety seeking behavior in a richer context. We propose using a modified MDCEV model to investigate the effects of satiation and state dependence in the context of snack consumption and estimate the model using panel data on individual consumption of snacks. Prior work that employed scanner data at the household level could not separate intra-household heterogeneity from true variety seeking. In contrast, we use individual consumption data collected using hand-held devices. We model consumers' choices from a variety of snack categories and are able to separate the effects of satiation, intrinsic utility, and state dependence and understand the effect of covariates that affect each aspect. We find evidence that consumers seek brand variety more than category variety within a day across time-periods but are habitual across days at the same time-period. Satiation varies across snack categories and across dayparts. Modeling satiation and state dependence improves the model fit considerably relative to the base model.

2.1 INTRODUCTION

Snacks account for about 25 percent of food consumption (Yoquinto 2011), so they are an important source of nutrients. Moreover since snack categories such as cakes, pretzels, cookies, potato chips, popcorn and candy bars are commonly regarded as unhealthy and causes of obesity, it is important to understand snack consumption.[1] Specifically, while habit, variety seeking and satiation have been found to be important features of meal consumption, it is not clear that the results for meals, in general, will apply to snacks. For example, snacking behavior may be different from consuming meals because snacks are available in many varieties and can be consumed in small amounts at a point in time. Though snacking accounts for a substantial portion of food consumption and involves consumption of a number of foods that are considered to be unhealthy, there is a lack of evidence about patterns of snack consumption.

We seek to understand whether variety seeking, or habit governs snack consumption decisions both within a day and across days, and to discover the role of satiation in generating variety seeking and habitual behavior. Variety seeking is a desire to change behavior because of satiation, boredom, or some other cause (McAlister 1982). For food, variety seeking often results from sensory-specific satiety, which refers to a sharp decline in the pleasantness and taste of food just eaten (Rolls 1986, Inman 2001). Satiation, more general than satiety, refers to diminishing marginal utility as more is consumed. Habit is defined as a context-response association that

[1] https://www.healthline.com/nutrition/20-foods-to-avoid-like-the-plague
https://healthyeating.sfgate.com/average-calorie-intake-human-per-day-versus-recommendation-1867.html

people learn as they frequently perform actions in stable choice environments and can be measured by the effect of past behavior on future behavior (Ouellette and Wood 1998).

We analyze patterns of snack consumption using a rich panel dataset on consumption of snacks by individual consumers in their homes. Since accessible panel data on snack consumption is scarce (most data are proprietary), our data is unique. A rolling panel of 341 randomly selected individuals recorded their entire snack consumption over a period of 14 days using mobile devices. The data supplier recruits new panels each week and the data cover a period of three years. Since consumption is measured at an individual level, we avoid intra-household heterogeneity, a known limitation of variety seeking literature based on household scanner data-based choice models. A possible drawback relative to scanner data is that we do not observe the effect of prices and promotions. However, most snacks can be stockpiled and consumed out of inventory, and so prices are unlikely to have a major effect on at-home consumption in a two-week period. In contrast to past research on variety seeking across brands, we focus on category choice and consumption for reasons we elaborate on later.

Unlike in brand choice models, in a snacking context, there are additional modeling challenges. Consumers may consume more than one snack on a given occasion, a phenomenon labeled as *multiple discreteness*. Consumption of multiple items at a given time period occurs in many other contexts such as entertainment products (video games, television shows etc.), magazine subscriptions, and mobile app usage. In the presence of multiple discreteness, standard choice models such as multinomial logit or probit are no longer appropriate. Further, when consumers simultaneously decide on what to consume and how much to consume, we need a model to account for both choice and quantity decisions. We address these challenges by developing an extension of the multiple discrete-continuous extreme value (MDCEV) model developed by Bhat (2005) to accommodate both choice of multiple snacks on a given occasion, and quantity consumed on that occasion.

Though much of the variety seeking literature focuses on brand choice, we focus on category choice across 14 categories of snacks. This is because we are interested more in understanding general consumption patterns of consumers, than on factors associated with brand choice. This focus is consistent with many other studies of food consumption, e.g., Inman (2001), Khare and Inman (2006, 2009), Haws, et al. (2017). The focus on categories also resolves a practical problem: the number of brands in these 14 categories is more than 500, making it unwieldy to estimate a model with such a large number of alternatives. However, we are able to assess brand level variety seeking separately from category variety seeking.

When modeling quantity choice, how should one compare quantity across categories such as candy and chips or between cookies and ice cream? We resolved this by modeling calories consumed of each snack as the continuous decision variable in the MDCEV model. Specifically, we convert the quantity consumed for each snack into calories (kcal). This procedure is used by the USDA in computing its food energy measure for its daily diary surveys of food consumption (e.g., What We Eat in America, NHANES 2015-2016). Calories are a measure of the energy produced by food and have often been used as a dependent measure in studies of food consumption (Inman 2001; Khare and Inman 2009; Saksena and Maldonado 2017). Calories are also the most prominent information on nutrition labels (Tangari, et al. 2019) and consumers do consider calories when consuming food items.

In summary, we develop a variation of the MDCEV model (Bhat 2005, 2008) that builds on prior research on variety seeking and incorporates the following features:

- We model snack category choice and calorie consumption in a unified model that handles multiple discreteness. To the best of our knowledge, this is the first application of the MDCEV model to understand variety seeking.
- We model satiation with each category and examine factors that affect satiation.
- We include state dependence of two types – within a day, and across days at the same time, for both brand and category. Thus, there are four state dependence terms to understand the effect of habit and variety seeking.
- We study the wearout effects of state dependence with the passage of time.
- We consider the effect of different dayparts within a day on both utility and satiation.
- We control for unobserved heterogeneity across panelists in both baseline utility and in satiation.

We estimate the model using individual panel data on snack consumption.

The issues that we study have important managerial implications. The relative magnitude of the effects of category state dependence and brand state dependence can assist managers to decide on whether to offer increased variety by developing new brands or new snack categories or both. Evidence of variation in snacking behavior over dayparts can help in advertising by associating the right snacks with the right time period. A good understanding of the factors that affect satiation can help firms to develop optimal package sizes for their snacks. Similarly, factors that strongly affect both choice and amount consumed would allow a firm to target the heavy snackers appropriately. At the same time, our analysis could provide insights into potential ways to limit obesity, an independent variable in our study. For instance, one could evaluate the reduction in calories by switching consumption dayparts or by switching snack categories. Thus, we propose a single model to derive multiple managerial and policy insights.

One key finding is that consumers seek brand variety within a day and to a lesser degree category variety. Across days (at the same daypart), we find habitual behavior for both category and brand. For instance, we find consumers consume the same kind of snacks at tea-time across days. The estimates also allow us to sort snack categories by the degree of satiation and to assess the influence of various factors on satiation. We find evidence that satiation is affected by age and time of day. Younger (<18) and older (>65) consumers exhibit lower satiation than the middle-aged. Also, consumers with higher BMI exhibit lower satiation. Further, consumers have lower satiation during the early part of the day (i.e., between breakfast and lunch) and higher satiation during post dinner snacking. In addition to the above results, we report the effect of weight, age, and gender on preferences for different categories of snacks.

We organize the remainder of the paper as follows. In Section 2, we review relevant literature. We provide relevant background information and describe the econometric model in Section 3. We provide details of our data in Section 4 and details of estimation in section 5. In Section 6, we present the results and highlight the key areas of interest. In Section 7, we discuss implications and limitations of our work and directions for future research. We conclude in section 8.

2.2 LITERATURE REVIEW

2.2.1 General literature

An important research issue in past research is to examine which of the two types of state-dependence - habit or variety seeking - is stronger in affecting snack choices. Habit, variety seeking, and satiation have been studied separately by marketers and researchers for a number of years. Literature on variety seeking behavior demonstrates multiple drivers such as satiation of attributes (McAlister 1982, McAlister and Pessemier 1982, Kahn 1995), satiety (Inman 2001), contextual factors (Yang et al. 2002), and consumer learning or search behavior (Dubé et al. 2010). Contextual factors refer to the characteristics of the snacking occasion such as whether a snack is eaten by itself or with other items and whether the consumer is eating with others or eating alone.

Since consumers may snack multiple times *within a day*, they may satiate on attributes and seek greater variety. So, one might expect to observe variety seeking, at the least, within a day since the time elapsed between two snacking occasions is short. On the other hand, the nutrition literature suggests that there are repetitive patterns to food consumption behavior across days, based on physiological needs at different times of the day (Marano 1993). This indicates that consumption at specific times of day across different days may be habitual, but that variety seeking may take place within a day.

Khare and Inman (2006, 2009) used diary panel data on household food consumption collected each day over two-week periods in 1998 and 1999 to examine this conjecture about habit and variety seeking. The 2006 study examined carryover habit, which is the tendency to consume the same mix of nutrients at the same meal each day compared to the mix within a day. Using separate equations for each of 6 nutrients, the authors found this to be the case, and that the carryover habit was strongest for breakfast. Khare and Inman (2006) focused on habitual behavior and did not devote specific attention to variety seeking.

Consistent with Marano (1993), Khare and Inman (2009) showed that consumers are habitual in their choice of meals across days but seek variety within a day. They found that food consumption may depend on the time interval (within a day or across days at the same daypart). They used the theories on habit formation and daily bracketing behavior in food consumption (Baumeister 2002) to support their hypotheses. Since they did not consider snacks separately, it leads to the interesting question whether consumption of snacks exhibits the same pattern.

While Khare and Inman (2009) focused on habitual behavior, Haws et al. (2017) presented a longitudinal study of the relation between variety of food choices and weight loss. They defined variety as the number of food items consumed in different time periods (daily or cumulative) and found that daily variety (but not cumulative variety) had a positive association with weight loss. They also found that episode-specific variety (e.g., variety in breakfast or lunch) rather than overall variety affected weight loss. The study emphasizes the need to study variety both within a day and across days.

There is an extensive experimental literature on factors that may affect satiation. Some of these factors are snacking as a reward for engaging in an unpleasant activity (Werle et al. 2015), self-control (Haws and Redden 2013), attention and distraction (Galak, et al. 2012, Hock and Bagchi (2017), categorization (Lasaleta and Redden 2018), availability (Sevilla and Redden 2014), packaging (Madzharov and Block 2010). A summary of the psychology literature related to satiation is presented by Galak and Redden (2018).

Girju and Ratchford (2019) examined the relationship between portion size, package size and contextual factors and snack consumption for seven snack categories. Consistent with previous literature, they found that snack consumption increases with portion size and package size, and is affected by contextual factors, such as snacking alone or watching TV. They used linear regressions and did not consider habit, variety seeking or satiation.

2.2.2 Econometric models to study habit and variety seeking

One of the consistent findings in variety seeking research using scanner data is that consumers exhibit considerable inertia in their brand choice (Seetharaman et al.1999, Dubé et al. 2010). The brand choice models incorporate state-dependence, which is the effect of a consumers' past brand purchase on their current utility. A positive value of the state dependence parameter indicates inertia or habit while a negative value indicates variety seeking behavior (Chintagunta 1998, Seetharaman et al. 1999, Trivedi et al. 1994, Dubé et al. 2010). Seetharaman et al (1999) find that households are inertial in product categories like toilet tissue, ketchup, peanut butter, and stick margarine but seek variety in canned tuna while Dubé et al (2010) find inertial effects in margarine and refrigerated orange juice. This suggests that observed variation in brands purchased by a household may be explained by marketing mix or contextual factors but there is little empirical evidence for variety seeking in the above categories.

As noted previously, a limitation of scanner data is that purchases are recorded at a household level. Households may purchase different brands due to variation in brand preferences within members of a household and this could be interpreted as evidence of variety seeking behavior. This confound can be resolved by analyzing individual consumption. Thus, a contribution of our study is that we use individual level consumption data on snacks to obtain a clearer understanding of variety seeking behavior.

The multinomial logit (MNL) based on random utility maximization (McFadden, 1980) has been a popular method to model discrete choice since Guadagni and Little (1983) introduced it to marketing. The model is appropriate to model a customer choice when the customer chooses one alternative among a set of choices. But, when customers choose multiple alternatives at a single occasion as when choosing two or more brands of yogurt, we face a situation termed *multiple discreteness* and the multinomial logit model is not appropriate.

Hendel (1999) first presented a solution to multiple discreteness and used data on personal computers to study return on investment of computerization. Other examples of multiple discreteness include choice of financial portfolios (stocks, bonds, gold, real estate), mobile apps, entertainment products (music, movies, TV shows) and software downloads. Kim, Allenby and Rossi (2002) first developed a microeconomic model to handle multiple discreteness and estimated it using yogurt scanner data. Dubé (2004) developed an alternate model of demand for

Table 2.1A. ***Comparison of Model Features***

Paper	Habit / Variety-Seeking	Satiation	Quantity Choice	Unobserved Heterogeneity	Multiple Discreteness
McAlister (1982)	✓	✓			
Seetharaman et al. (1999) Dubé et al. (2010) Trivedi et al (1994)	✓			✓	
Hendel (1999) Kim et al. (2002) Hasegawa et al (2012)		✓	✓	✓	✓
Bhat (2005, 2008)		✓	✓	✓	✓
Khare and Inman (2009)	✓		✓	✓	
Our Study (2020)	✓	✓	✓	✓	✓

soft drinks, a category where consumers exhibit multiple discreteness. Hasegawa et al. (2012) used the above model frameworks to demonstrate dynamic variety seeking, the idea that people may become more (or less) variety seeking over time. While the models represent a major innovation in choice models, they are complex and are not easy to estimate with many alternatives, since they assume a Normal distribution for the error term. The number of integrals for estimation increases with the number of alternatives considered.

Bhat (2005) developed the multiple discrete continuous extreme value (MDCEV) model that models both choice and quantity, has a closed-form solution, and is much simpler to estimate, compared to the models of Kim et al (2002) and Dubé (2004). Bhat (2005) used the extreme value distribution and developed the model using the random utility maximization (RUM) framework to provide an easy to estimate model with a large number of alternatives. The authors

Table 2.1B. ***Summary of Literature***

Paper	**Dependent Variables**	**Key Predictors**
McAlister (1982)		Product Attributes
Seetharaman et al. (1999) Dubé et al. (2010) Trivedi et al (1994)	Brand choice	Price, Feature, Display
Hendel (1999) Kim et al. (2002) Hasegawa et al (2012)		Marketing mix
Bhat (2005, 2008)	Category choice, Usage	Individual Characteristics
Khare and Inman (2009)	Meal Calories	Past Consumption Choices, Time
Our Study (2020)	Category choice, Snack calories	Past Choices Individual, Product Characteristics, Time

showed that if a single brand were purchased on each occasion, their MDCEV model would reduce to the well-known multinomial logit model. Further, the model is able to quantify satiation with quantity consumed. As with the logit model, MDCEV model was extended to include unobserved heterogeneity and has been applied in a number of contexts, primarily in transportation research and urban planning (Spissu et al. 2009; Bhat and Sen 2006, Bhat et al. 2009). We present a comparison of econometric model features in Table 2.1A. In Table 2.1B we present the summary of literature and the variables used across key papers.

2.3 ECONOMETRIC MODEL

The MDCEV model is well suited for examining drivers of snack choice as well as calories consumed because it allows researchers to study satiation with quantity, and at the same time model variety seeking or habitual behavior. Therefore, one goal of our study is to demonstrate how to use the MDCEV model, a relatively new methodology, to understand variety seeking (or habitual behavior) in a category where consumers exhibit multiple discreteness and simultaneously decide how much to consume.

An advantage of the MDCEV model over choice models is that it can capture satiation with quantity separately from the intrinsic utility that determines choice. This allows us to tease out the effect of satiation from other reasons for switching. Further, we can understand the effect of factors that affect satiation and factors that affect utility separately. Therefore, we employ the MDCEV model to address the following issues: i) Does satiation depend on the time of snacking within a day? Is it different for different snack categories, nutrients, age groups, and genders? ii) Do consumers seek greater variety (or are driven by habit) when choosing a snack category (or brand)? In other words, what is the effect of category- and brand- state dependence on utility? iii) How does the effect of state dependence vary within a day, and across days? As noted earlier, Khare and Inman (2006, 2009) empirically show that consumers seek variety in their meals within a day but exhibit inertia in their consumption of meals across days. We study whether the above effect holds for consumption of snacks as well.

We assume that a consumer obtains utility *U*(c_j), from the consumption of a certain amount of calories in category *j* (c_j) subject to a budget constraint. The utility function proposed by Bhat (2005) to model both the utility and satiation associated with snack consumption is:

$$U(c_j) = \sum_{j=1}^{J} \frac{\gamma_j}{\alpha_j} \psi_j \left\{ \left(\frac{c_j}{\gamma_j} + 1 \right)^{\alpha_j} - 1 \right\} \tag{1}$$

From our perspective, the individual has a budget constraint $\sum_1^J c_j = C$, where C is the total calories consumed. We initially consider that the consumers choose only from snack categories and estimate a model. This assumption (no outside good) implies that substitution happens only between snack categories. We then allow for the consumer to choose from an outside good, which is calories consumed from non-snack categories (regular meals). By adding an outside good, we relax the assumption of substitution between snack categories alone. Now, consumers are allowed to substitute between snack categories and the outside good (Kim et al. 2002). However, we don't observe the consumption amount for the outside good, therefore, we use the Mifflin-St Jeor equation (Mifflin et al. 1990). This equation is widely used across fields such as nutrition and obesity to estimate the amount of calories recommended for an individual based on factors such as gender, age, height, weight.

Of the J=14 categories in our paper, a consumer may choose one or more categories to consume at a given occasion. ψ_j represents the baseline marginal utility from choosing category *j* and is assumed to be a linear function of customer characteristics, product nutrients, state dependence terms and time of day (measured as dayparts). The parameter α_j ($0 < \alpha_j < 1$) is the satiation parameter that indicates the rate of diminishing marginal utility from consuming more of alternative *j*. γ_j is a translation parameter in Bhat's original specification but is set to 1 since it cannot be identified separately from α_j (Bhat 2005, 2008). Thus, the utility function of customer *i*, choosing c_{it} calories of category *j* at occasion *t* can be written as:

$$U_{it}(c_{it}) = \sum_{j=1}^{J} \frac{1}{\alpha_j} \psi_{ijt} \{(c_{it} + 1)^{\alpha_j} - 1\} \tag{2}$$

The values of baseline utility and satiation parameters determine how much of category *j* a consumer chooses. High values of baseline utility indicate a high preference for the category. High values of satiation parameter α_j indicate lower satiation and indicate a smaller decline in the rate of consumption as quantity increases. The baseline marginal utility function for choice decision can be parametrized as $\exp(\beta' x_j + \varepsilon_j)$, where x_j is a vector of covariates and intercepts for each category *j*. Bhat (2008) assumes the error term ε_j to be independently and identically distributed (i.i.d.) extreme value distribution.

We expect preferences and consumption of snacks to be affected by individual characteristics such as age, gender, and weight. The baseline utility may also be affected by nutrients in snacks such as fat, carbohydrates, protein and fiber. We also include dayparts as covariates since the nutrition literature suggests a need for different nutrients at different times within a day (Marano 1993).

To accommodate variety seeking or inertial behavior, we extend Bhat's model by including four state dependence terms - two each for brand and for category. As in Khare and Inman (2009), we include two types of state-dependence - i) across different time periods within a day (termed *time dependence*) and ii) across days but at the same time period (termed *day dependence*). In Figure 2.1, we graphically explain the two terms – day dependence and time dependence.

Thus, our utility function ψ_j can be written as follows:

$$\psi_j = \exp\left(\beta_j \boldsymbol{x_j} + \delta_k * \boldsymbol{S_{it}} + \delta_{1k} * ln(t+1) * \boldsymbol{S_{it}} + \varepsilon_j\right) \quad (3)$$

In Equation (3), $\mathbf{x_j}$ is a vector of covariates. We represent the four state dependence terms with the vector $\mathbf{S_{it}}$ in equation 3. Brand time dependence in $\mathbf{S_{it}}$ takes the value 1 if a given brand was consumed in the previous daypart and is 0 otherwise. Similarly, brand day dependence takes the

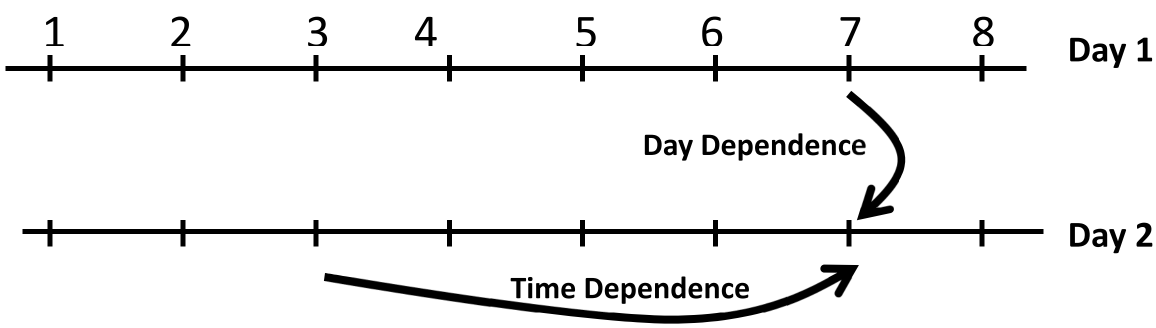

Figure 2.1. ***Time and Day Dependence***

value 1 if a given brand was consumed in the same daypart on the previous day and is 0 otherwise. Category state dependence terms are defined in a similar manner. Note, $\mathbf{S_{it}}$ is a vector that includes four terms - brand time-dependence, brand day-dependence, category time-dependence and category day-dependence. If δ_k is positive it means that a consumer's utility for repeating a snack increases if it was consumed earlier and we infer habitual or inertial behavior.

If δ_k is negative, we infer that the consumer seeks variety since previous consumption lowers utility for a subsequent consumption of the same snack.

Trivedi et al. (1994) and Seetharaman et al. (1999) show that the effect of state dependence may decay over time, referred to as *wearout* effects. Immediately after a consumer eats a snack, its utility in the next instant goes down but increases slowly with the passage of time. To capture the effect of the gap between consumption occasions on state dependence terms, we interact S_{it} with time delay as in Seetharaman et al. (1999). One expects that with passing of time between snack occasions (i.e., increased delay), consumers may not mind repeating the same alternative (i.e., will exhibit inertia). So, as delay increases, we expect a positive state dependence parameter (δ_{1k}). As in Seetharaman et al. (1999), we use the functional form log (t+1) to capture delay, where *t* represents the time interval between two consecutive snack occasions. If a consumer eats two or more snacks at the same time, *t* can be 0 and so we add 1 before we take logarithm. We use log (t+1) and log (d+1) to denote the decay over dayparts (t) and over days (d) respectively. As in Bhat (2005) we restrict α_j to lie between 0 and 1 by adopting the following logistic functional form.

$$\alpha_j = \frac{1}{1+\exp(-\phi_j)} \tag{4}$$

α_j = 1 implies there are no satiation effects and constant marginal utility (Bhat, 2005). A lower value of α_j indicates greater satiation as it reduces the utility for each additional quantity consumed. To evaluate the effect of various factors on satiation, we express ϕ_j as follows:

$$\phi_j = \omega_j + \tau_j{}' * \boldsymbol{L_j} \tag{5}$$

where ω_j is a constant that represents the average satiation for category *j* and τ_j represents the effect of covariates in $\boldsymbol{L_j}$. We use individual characteristics, nutrients, and daypart dummies as covariates to explain satiation with quantity.

For identification purposes, we designate one of the categories (ice cream/gelatin) as the base alternative and utility from consuming the remaining 13 alternatives is relative to the base category. The utility function for the model with the outside good is written as:

$$U_{it}(c_{it}) = \frac{1}{\alpha_1}\psi_{i1t}c_{i1t}^{\alpha_1} + \sum_{j=2}^{J}\frac{1}{\alpha_j}\psi_{ijt}\left\{\left(c_{ijt}+1\right)^{\alpha_j}-1\right\} \tag{6}$$

To complete the specification, we allow for unobserved heterogeneity in the intercept of the baseline utility and in the satiation parameter for each category. We use a random-effects specification and assume the heterogeneity to follow a multivariate normal distribution. The variance of the error term captures unobserved intra-individual heterogeneity, across choice occasions (Spissu et al, 2009). Setting up the Lagrangian and solving for the optimal calorie allocations to each good and applying the Kuhn-Tucker (KT) conditions, we arrive at:

$$\mathcal{L} = \sum_{j=1}^{J}\frac{1}{\alpha_j}\psi_{ijt}\left\{\left(c_{ijt}+1\right)^{\alpha_j}-1\right\} - \lambda\left(\sum_{1}^{J}c_{ijt}-C\right) \tag{7}$$

The optimal consumption satisfies the budget constraint and the first order conditions from the above equation. As the quantity for one of the goods is known if we know the budget and that of the *J-1* other goods, we need to estimate only *J-1* of the c_{ijt}^{*} (optimal consumption quantities). We designate V_1 as the observed utility from the first good and V_j as the observed utility for the *j*[th] good. We then have, $V_j = \boldsymbol{\beta_j x_j} + \delta_k * \boldsymbol{S_{it}} + \delta_{1k} * ln(t+1) * \boldsymbol{S_{it}} + (\alpha_j - 1)\ln(c_j + 1)$. Further from the KT conditions, $V_j + \epsilon_j = V_1 + \epsilon_j$, if $c_{ijt}^{*} > 0$ and $V_j + \epsilon_j < V_1 + \epsilon_j$, if $c_{ijt}^{*} = 0$. The intuition is that consumption chooses a non-zero quantity from a good, if the utility derived is at least as much as that of the first good, otherwise the quantity consumed is set to 0. Assuming that ϵ_j is i.i.d. extreme value, the probability that an individual would choose from M of the J alternatives can be written as,

$$P(c_{i1t}, c_{i2t}, \dots, c_{iMt}, 0,0, \dots, 0) = \prod_1^M \frac{1-\alpha_j}{c_{ijt}+1} \sum_1^M \frac{c_{ijt}+1}{1-\alpha_j} \prod_{j=1}^M \frac{e^{V_j}}{\sum e^{V_k}} (M-1)! \tag{8}$$

The probability expression for the case with an outside good is identical to equation (8). The outside good is treated as the first or the base good. The log-likelihood function can be written as,

$$LL = \log \sum \left(\prod_1^M \frac{1-\alpha_j}{c_{ijt}+1} \sum_1^M \frac{c_{ijt}+1}{1-\alpha_j} \prod_{j=1}^M \frac{e^{V_j}}{\sum e^{V_k}} (M-1)! \right) \tag{9}$$

The probability expression for the model with random intercepts in utility and satiation is written as,

$$P(c_{i1t}, c_{i2t}, \dots, c_{iMt}, 0,0, \dots, 0) = \int \prod_1^M \frac{1-\alpha_j}{c_{ijt}+1} \sum_1^M \frac{c_{ijt}+1}{1-\alpha_j} \prod_{j=1}^M \frac{e^{V_j}}{\sum e^{V_k}} (M-1)! \; dF(\zeta) \tag{10}$$

where, $\zeta \sim N(0, \Sigma)$.

2.4 DATA

The data comes from snacking records provided by a random sample of participants recruited by a large US based snack manufacturer. These participants use a mobile device to record their snack consumption activity for a period of fourteen days. They were asked to report their snacking behavior on the device at the moment of consumption. Hence, our data is recorded virtually in real-time in subjects' natural environments, which helps minimize memory loss, recall bias, and social desirability bias relative to surveys and experiments. At the end of the 2-week participation, the participant mailed the device back, and the data was downloaded and validated. Participants entered information such as demographics (age, gender, race, region, household size, height, weight, income, race, marital status, education, and location), and report consumption activity – brand name and quantity consumed of each snack at each occasion.[2]

In our sample, we have 1811 participants who report 21145 snacking occasions during the period 2008 to 2011. Based on the frequency of consumption we selected the top 14 categories of snacks. We used a sample of consumers that snacked at least 10 times within these 14 categories during the two-week period. In the final estimation sample, we have 341 panelists consuming a total of 5327 snacks in a 14-day period (i.e. about 16 snacks per person). Consumers exhibit multiple discreteness on about 13% of the occasions. The fourteen snack categories are - chips, chocolate/candy, cookies, crackers, ice cream/gelatin, pastries/donuts, cakes, energy bars, nuts/seeds, popcorn, pretzels/snack mix, puffs, yogurt and other snacks. The category "other snacks" includes meat-based snacks (e.g. beef jerky). The snack taxonomy is based on standard industry practice. We use ice-cream/gelatin as the base category and all comparisons of estimates are relative to this category.

Based on quantity consumed at each occasion and the nutrition label information, we calculated the total calorie intake for an individual for each occasion as:

$$c_{it} = \sum_{k=1}^{K} Cal_k * Q_{ik} \tag{11}$$

i = 1, ..., I (indexes the individual),

k = 1, …, K (category consumed)

$\mathrm{Cal}_{\mathrm{k}}$ = calorie per serving from category *k*

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[2] Though the data was collected by a market research firm using state-of-the art procedures, it is still subject to the usual data collection problems of bias in reporting. We believe the effect of attrition and drop-out rates are small.

Q_{ik} = quantity consumed (in servings) by individual *i* in category *k*

c_{it} = Total calories consumed at an occasion *t* by individual *i*

Table 2.2A shows the key demographic variables that affect snacking. Our sample of 341 individuals is split roughly equally between males and females. Based on the Body Mass Index (BMI), we find that 37% of the sample are normal weight, 30% over-weight, and 33% obese. Panelists "18 and under" and those "65 and over" in age consumed fewer snack calories than respondents who are age 19-64. Obese panelists do not appear to consume more calories per occasion than others. Table 2.2B shows the percentage frequency and average calories consumed

Table 2.2A. ***Key Demographic Characteristics***

Demographic Characteristics	**Proportion of Sample**	**Average Calories per Occasion**
Gender		
Male	54.80%	187.4
Female	45.20%	189.7
Age		
<=18	10.90%	179.1
19-64	69.50%	192.1
>=65	19.60%	180.8
Obesity		
Normal Weight	37.00%	191
Overweight	30.20%	186.6
Obese	32.80%	187.2
Total Individuals	341	

across the 14 categories of snacks. Chips, chocolate/candy and cookies are the most snacked items. Cakes and pastries/donuts/muffins have the highest calories per occasion. In Table 3, we see that each day is divided into 6 dayparts – breakfast (BF), between breakfast and lunch (BL), lunch (L), between lunch and dinner (LD), dinner (D) and after dinner (AD). We see that about 27% of snack items are consumed at mealtimes, and about 73% are consumed between meals.

About 60% of snacks are consumed 'between lunch and dinner' and 'after dinner'. Table 2.4 presents a breakdown of the percentage of consumption occasions by daypart. Pastries, donuts, muffins and breakfast bars account for the highest percentage of consumption at breakfast, while

Table 2.2B. ***Calorie Consumption by Category***

Category	**Percentage Frequency**	**Average Calories**
Breakfast Bars	4.86 %	145.2
Cakes	3.15 %	203.0
Chocolate Candy	13.72 %	175.0
Chips	15.00 %	148.4
Cookies	10.00 %	163.7
Crackers	6.53 %	135.4
Ice cream / gelatin	7.01 %	136.8
Nuts / Seeds	9.31 %	187.0
Others	7.90 %	164.5
Popcorn	4.41 %	145.9
Pastries / Donuts / Muffins	6.96 %	234.6
Pretzels / Snack Mixes	4.34 %	127.8
Puffs	4.37 %	163.2
Yogurt	2.44 %	154.6
Number of snack occasions	5327	

Table 2.3. ***Consumption by Dayparts***

Daypart	**Average Calories per Occasion**	**Percentage of Occasions**
Breakfast (BF)	189.5	10.66%
Between Breakfast & Lunch (BL)	167.4	12.67%
At Lunch (L)	151.1	12.39%
Between Lunch & Dinner (LD)	161.7	27.65%
At Dinner (D)	163.5	4.07%
After Dinner (AD)	163.1	32.55%

Table 2.4. ***Percentage of Consumption Occasions for each Category by Daypart***

Category	Breakfast	Between Breakfast & Lunch	At Lunch	Between Lunch & Dinner	At Dinner	After Dinner
Breakfast Bars	**15.4%**	7.6%	2.6%	3.6%	1.2%	2.6%
Cake	4.7%	3.2%	1.9%	2.9%	4.6%	3.7%
Chocolate Candy	3.3%	**12.4%**	5.3%	**17.6%**	**13.7%**	**17.1%**
Chips	3.7%	**10.9%**	**37.6%**	**14.8%**	**28.0%**	**11.1%**
Cookies	7.4%	**9.4%**	**9.2%**	**9.2%**	**9.0%**	**12.2%**
Crackers	3.9%	6.1%	**9.8%**	**7.3%**	**6.5%**	5.5%
Ice-Cream Gelatin	0.8%	4.2%	3.7%	5.8%	5.1%	**12.8%**
Nuts & Seeds	**8.5%**	**10.3%**	3.6%	**13.6%**	4.9%	**8.2%**
Others	**11.2%**	8.0%	**9.1%**	6.8%	**11.8%**	7.1%
Popcorn	0.9%	3.4%	1.5%	3.7%	2.2%	7.2%
Pastries Donuts and Muffins	**28.3%**	**9.9%**	2.3%	4.2%	2.3%	3.9%
Pretzels and Snack Mixes	1.1%	4.6%	2.4%	5.5%	4.9%	4.3%
Puffs	0.8%	3.8%	4.4%	3.0%	3.5%	1.9%
Yogurt	**10.0%**	6.2%	**6.6%**	2.0%	2.3%	2.4%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

chips account for the highest percentage of consumption at lunch and dinner. Candy is the most popular snack between meals, followed by chips, cookies and nuts and seeds. Ice cream is popular after dinner. The five most frequently consumed categories are highlighted in bold

2.5 MODEL ESTIMATION AND RESULTS

We use simulation techniques to maximize the log-likelihood function. After testing for stability of the estimation procedure and sensitivity of the parameter estimates, we decided to use 125 Halton draws (as in Bhat, 2005). Since the mean of the calorie variable was much higher than the means of other covariates, we scaled the variable using Box-Cox transformation (Yeo and Johnson, 2000) to ensure that the model converges smoothly, and the Hessian does not fail to invert.

We estimated two models – i) an MCDEV model with no unobserved heterogeneity and ii) an MCDEV model with heterogeneity.In Table 2.5, we report log-likelihood, AIC, and BIC values for several models. The full MDCEV model with control for unobserved heterogeneity (Model 1) has a log-likelihood value of -14198.48. If we do not account for unobserved heterogeneity (Model 2), the log-likelihood worsens by 77. A likelihood ratio test rejects Model 2 (the base model) with no unobserved heterogeneity. To examine the contribution of different model features to model fit, we estimated several MDCEV models without heterogeneity and compared the results to Model 2. Ignoring satiation (by fixing the alpha parameter to 1) yields a log-likelihood value of -18020.12 which is worse than that of model 2, by 3745. Ignoring state dependence terms also yields a worse log-likelihood than model 2 by 2580. Similarly, ignoring dayparts or demographic characteristics or product nutrients worsens the log-likelihood by about

Table 2.5. ***Comparison of Model Fit***

Specifications	**N**	**Parameters**	**Log-lik.**	**AIC**	**BIC**
Model 2 without satiation	5327	93	-18020.12	36226.24	36838.24
Model 2 without Nutrients (Fat, protein etc.) and dayparts	5327	103	-15770.93	31747.86	32425.66
Model 2 without dayparts	5327	111	-15620.94	31463.88	32194.32
Model 2 without nutrients	5327	113	-15675.00	31576.00	32319.60
Model 2 without state dependence	5327	115	-16855.93	33941.86	34698.62
Model 2: Full model without unobserved heterogeneity	5327	121	-14275.56	28793.12	29589.37
Model 1: Full Model with unobserved heterogeneity	5327	144	-14198.48	28684.96	29632.56

1400. This indicates that modeling satiation and state dependence improves the model fit much more relative to other elements. Modeling dayparts, nutrients, and demographics also leads to a considerable improvement. Unobserved heterogeneity affects model fit to a much smaller degree. AIC and BIC values (that consider the number of parameters) also support the above pattern.

In Table 2.6, we report estimates of MDCEV model with controls for unobserved heterogeneity. We interpret parameters of the full model reported in Table 6. Note that ice cream/gelatin is the base level and we show significant parameter estimates in bold (significant at 95% confidence level). The first row in Table 6 shows the estimates of the intercept for each category which captures the average intrinsic preference for each snack category. We observe that candy, chips, cookies, nuts/seeds have non-significant intercepts indicating that they do not differ significantly from ice cream/gelatin in terms of individuals' preferences. The remaining nine categories have negative significant coefficients, indicating that these categories are less preferred relative to the above five categories. The least preferred categories of snacks are "Other" (or meat snacks), yogurt, cheese puffs, and breakfast bars in that order.

Our main results relate to the effect of state dependence on the choice of snack categories and of brands both across days and across dayparts within a single day. We expect that individuals will be inertial across days but may be variety seekers within a day. The state dependence parameter captures the inter-temporal dynamics of consumer choices. A positive coefficient indicates inertial or habitual behavior in consumption. On the other hand, a negative coefficient indicates a variety seeking tendency. We estimated a single state dependence parameter for all 14 categories, for two reasons. First, we believe that habitual/variety seeking tendencies reflect an individual trait and may not vary significantly across snack categories. Second, we preferred parsimony in estimation.

In Table 2.6, we find that the day dependence (i.e. state dependence across days) is strongly positive for categories (β=2.06) and for brands (β=1.69), indicating that consumers are habitual in their behavior over different days but at the same daypart. In other words, consumers prefer to repeat the same snack categories and brands across days at a specific time.

Table 2.6A. ***Parameters of the Full Model***

Log-Likelihood	-14198.48
No. of Observations	5327

Parameter	Ice-cream	Cakes	Candy	Chips	Cookies	Crackers	Breakfast Bars
Intercept Baseline Utility		**-1.029****	-0.034	-0.334	-0.295	**-0.568**	**-1.186**
Normal Weight		0.232	**0.509**	**0.432**	**0.481**	***0.363***	***0.361***
Obese		**-0.499**	0.154	**0.377**	0.247	0.267	**0.542**
Age <=18		0.088	**-0.897**	***-0.407***	**-0.474**	-0.021	-0.171
Age >=65		-0.051	-0.014	-0.111	0.123	***0.384***	0.182
Female		**-0.403**	**-0.48**	**-0.531**	**-0.425**	**-0.481**	0.164
σ_{RE}		**1.505**	**0.322**	**0.267**	**0.978**	**0.766**	0.601

** Bold numbers indicate significance at 95% confidence level (p<0.05)
* Bold number in italics indicate significance at 90% confidence level (p<0.10). Non-bold numbers are not significant at 90%.

This is consistent with consumers categorizing snacks as morning snacks, afternoon snacks and late-night snacks. This result is also consistent with findings in Khare and Inman (2006) who find that people are inertial across days with respect to meal choices. We conclude that habit is a stronger force governing snack choice across days.

Table 2.6B. ***Utility Parameters - Demographics***

Parameter	Nuts and Seeds	Others	Pop Corn	Pastries	Pretzels	Puffs	Yogurt
Intercept Baseline Utility	-0.387	**-2.247**	**-0.850**	**-0.658**	**-0.957**	**-1.578**	**-1.559**
Normal Weight	**0.454**	**0.476**	0.191	**0.435**	***0.360***	0.393	**0.442**
Obese	0.283	***0.429****	0.263	0.279	0.296	0.331	0.159
Age <=18	**-1.576**	-0.002	-0.110	0.086	-0.306	0.382	-0.299
Age >=65	**0.609**	0.287	0.124	0.014	-0.084	-0.513	**0.543**
Female	**-0.379**	0.229	-0.187	-0.126	-0.272	-0.276	0.089
σ_{RE}	**2.855**	1.152	0.723	1.431	1.272	0.685	1.490

Table 2.6C. ***Utility Parameters - Covariates***

Variable	Estimate
Day Dependence – Category	**2.065**
Time Dependence – Category	0.107
Day Dependence (Cat)* Log (Delay+1)	**0.663**
Time Dependence (Cat)* Log (Delay+1)	**-0.464**
Day Dependence - Brand	**1.693**
Time Dependence - Brand	**-0.498**
Fat	**0.178**
Carbohydrates	**-0.030**
Fiber	**0.366**
Protein	**-0.009**
Before & at Breakfast (BF)	**2.198**
Between Breakfast & Lunch (BL)	0.277
Between Lunch and Dinner (LD)	-0.274
After Dinner (AD)	**-1.178**
Weekend	-0.087

However, within a day, we expect to find evidence of variety seeking since the snack occasions are closer in time. We find that the state dependence coefficient for brand is significant and negative (-0.498) but is not significant for category (0.107). This suggests that within a day, consumers exhibit greater variety seeking behavior for brands than they do for categories. Compared to strong habitual behavior in category choice across days, consumers exhibit a lesser degree of habitual behavior within a day. We note that the day dependence parameter for brands is much larger than the time dependence parameter. The implication is that habit is a stronger driver of snack choices.

We also tested whether consumers exhibit greater variety seeking tendencies with respect to category choice as the time interval between snack occasions gets larger. We see that within a day as the time gap between snack occasions increases, state dependence for category choice is negative and significant (-0.46). This suggests that as the gap between snack occasions increases, it induces a certain degree of variety seeking behavior. However, across days for the same daypart, as the gap in number of days increases, day dependence coefficient is positive, indicating reinforcement of habit with delay. This suggests that across days, habit is a very strong force and delay only heightens desire for the familiar or favorite snack. This reinforces our argument that consumers exhibit variety seeking behavior within a day but are habitual across days. Time delay between snack occasions only reinforces this pattern.

Table 2.7A. ***Satiation Parameters***

	Ice-cream	Cakes	Candy	Chips	Cookies	Crackers	Breakfast Bars
Baseline (Raw)	-0.161	**1.174****	0.171	0.484	0.520	0.305	**0.949**
σ_{RE}		**0.062**	0.607	0.675	0.015	0.562	**0.445**

** Bold numbers indicate significance at 95% confidence level (p<0.05)
* Bold number in italics indicate significance at 90% confidence level (p<0.10). Non-bold numbers are not significant at 90%.

Table 2.7B. ***Satiation Parameters***

	Nuts	Others	Pop Corn	Pastries	Pretzels	Puffs	Yogurt
Baseline (Raw)	0.514	**-1.261**	**1.857**	**2.535**	0.056	***1.229****	-0.436
σ_{RE}	*not estimated*			0.897	1.504	0.743	0.267

The underlying reason for both behaviors could be the strong habit formation in consumption of snacks in which consumers learn to associate certain snacks with certain dayparts. We considered the effect of micronutrients - fat, carbohydrates, protein and fiber - on consumer preference for snacks. We find that consumers exhibit a significantly higher preference for fat and fiber and a significantly lower preference for carbohydrates and protein content in snacks.

The effect of dayparts on preferences suggest that individuals have greater utility for snacks at breakfast relative to mealtimes (i.e., lunch and dinner, which are the base levels). From Table 2.4, the categories that have the highest frequency during breakfast period are breakfast bars, pastries/donuts/muffins, and yogurt. We also find that there is a relatively lower utility for snacking after dinner compared to the utility for snacking at mealtimes. We do not observe any significant difference in utility for snacking on weekdays and weekends.

Table 2.7C. ***Satiation Parameters - Covariates***

Variables	Estimate
Age <=18	**0.577**
Age >=65	**0.506**
Female	-0.009
Normal	-0.252
Obese	**0.167**
Fat	**0.032**
Carbohydrates	**0.015**
Fiber	-0.084
Protein	-0.004
Before & at Breakfast (BF)	0.206
Between Breakfast & Lunch (BL)	**0.779**
Between Lunch and Dinner (LD)	-0.055
After Dinner (AD)	**-0.598**
Weekend	-0.057

The other main contribution of the model is the estimation of satiation parameters and factors that affect satiation. A large positive parameter indicates a relatively low satiation level implying greater consumption of calories per occasion in that category. A non-significant parameter indicates a medium level of satiation as compared to a negative coefficient.

From Tables 2.7A and 2.7B, we see that the baseline satiation parameters vary across snack categories. Low satiation categories include pastries/donuts/muffins, popcorn, cheese puffs, and cakes. On the other hand, high satiation categories include meat snacks (other). Ice cream, candy, crackers, pretzels, and yogurt represent an intermediate level of satiation since these coefficients are non-significant. Thus, the proposed model allows a firm to determine satiation levels of different snack categories. One can potentially estimate satiation parameters for different demographics for each category. We did not estimate such a model for the sake of parsimony.

In terms of factors that affect satiation (Table 2.7C), we find that both younger (≤18) and older consumers (≥65) exhibit a lower satiation relative to adults. That is, these two age groups consume a relatively greater number of calories of snacks per occasion than adults. Obese consumers exhibit lower satiation levels relative to normal and overweight groups. Consistent with the nutrition literature, we find that fat- and carbohydrates-rich snacks are relatively less satiating than protein- and fiber-rich snacks (Blundell and Rogers 1991). We also find evidence of differences in satiation across dayparts. Snacking between breakfast and lunch is associated with lower satiation relative to snacking at mealtimes, indicating that a greater quantity of snacks is consumed during this daypart than at mealtimes. Post dinner snacking is higher in satiation suggesting relatively smaller quantity intake. We do not find any difference in satiation on weekends relative to weekdays.

To get a complete picture of satiation, it is necessary to calculate the overall satiation parameter using covariates as well as the category-specific intercepts, as explained in Equations 4 and 5. We performed this calculation using the intercepts and average values of the covariates. The results are presented in Table 2.8. We sorted the different snack categories using average satiation parameter (α_j). Pastries/donuts and popcorn exhibit high α values (i.e. low relative satiation) suggesting greater consumption of calories. On the other hand, yogurt and 'other' snacks have low α values. The relative values of the satiation parameters (α_j) remain the same as outlined above for their intercepts, but adding the covariates shifts the location of satiation parameters upwards. Thus, the method allows a manager to assess satiation across categories. These are average predicted values of $\alpha_j = \frac{1}{1+\exp(-\phi_j)}$ where $\phi_j = \omega_j + \tau_j' * L_j$

Table 2.8. ***Average Satiation Parameter***

Category	Average α_j
Pastries Donuts and Muffins	0.948
Pop Corn	0.902
Puffs	0.831
Cakes	0.822
Breakfast Bars	0.788
Cookies	0.707
Nuts and Seeds	0.706
Chips	0.700
Crackers	0.661
Chocolate Candy	0.630
Pretzels and Snack Mixes	0.603
Ice-Cream Gelatin	0.550
Yogurt	0.482
Others	0.289

2.5.1 Effect of BMI on preferences

Based on BMI, individuals are classified as either normal, overweight, or obese. We use the overweight category as the baseline against which the utility for the other two groups is compared. In Table 2.6, we find that compared to overweight individuals, normal weight consumers consume significantly more calories in chocolate/candy, chips, cookies, pastries, yogurt, meat snacks and nuts/seeds categories. On the other hand, obese individuals do not prefer calories from cakes but do prefer chips, breakfast bars, and other meat-based snacks, when compared to overweight individuals. The evidence is consistent with conclusions in Macdiarmid et al., (1998) in which they show a negative relationship between higher BMI and intake of sugary foods.

2.5.2 Effect of Age on preferences

We wished to examine difference between youth, adults, and older individuals in terms of their preferences for different categories of snacks. Compared to the base group (adults aged 19-64 years), we find a lower preference for chocolate, cookies, and nuts and seeds among the younger individuals. At first glance, this seemed unusual since we expected that chips and candy are most attractive to children. However, on further reflection, parents and guardians may have a strong influence on children's snacking habits. The other categories have non-significant coefficients relative to ice creams. Older individuals exhibit a higher preference for nuts/seeds, yogurt, and crackers relative to adults. These preferences may be driven by greater health considerations at an older age.

2.5.3 Effect of Gender on preferences

Compared to males, females exhibit a lower preference in many categories of snacks such as cakes, chocolate/candy, chips, cookies, crackers, and nuts/seeds. The evidence points to the fact that males snack more than females in a number of popular snack categories. The results are inconsistent with those reported in earlier studies. For instance, Wansink et al., (2003) found that females had a higher preference relative to males in chocolate, candy and ice cream. Tuomisto et al., (1999) and Hetherington & MacDiarmid (1993) found that a majority of respondents (97% and 92% respectively) in their studies self-identified as "chocolate addicts" were female. Wardle et al (2004) found that females avoided salt compared to males in six European countries but did not find any significant difference between the gender groups in the US. Our results indicate that women do have a lower preference for salty snacks (i.e., chips, crackers, and puffs) as well as sweet snacks (cakes, candy).

The random effects parameters for the intercepts indicate that there is significant unobserved heterogeneity in baseline preferences in a number of categories. The greatest variation in preferences is in nuts/seeds, followed by cakes, pastries, and yogurt. This means that in these categories, intrinsic preferences are not homogeneous across consumers. The least variation is seen in ice cream/gelatin and chips categories suggesting that most consumers in our sample seem to uniformly like these snacks.

We do not find evidence of significant unobserved heterogeneity in satiation parameters across consumers. Of the 13 random effects parameters only one is significant and that too at a 90% confidence level. The greatest variation in baseline satiation parameter is seen in the chocolate/candy category. Tables 2.9 and 2.10 shows the results for the model without outside and no unobserved heterogeneity.

Table 2.9A. ***MDCEV with No Outside Good – No Unobserved Heterogeneity***

Log-Likelihood	-14275.56
No. of Observations	5327

Parameter	Ice-cream	Cakes	Candy	Chips	Cookies	Crackers	Breakfast Bars
Intercept Baseline Utility		**-0.8642****	0.129	-0.0725	-0.2311	**-0.5503**	**-1.2135**
Normal Weight		0.1159	**0.4182**	**0.4502**	**0.4529**	***0.2914***	0.3072
Obese		**-0.5101**	0.1074	**0.3826**	0.2303	0.2245	**0.5202**
Age <=18		0.0547	**-0.9011**	-0.3075	***-0.4447****	-0.0141	-0.1554
Age >=65		-0.0152	-0.0014	-0.0173	0.1262	**0.3789**	0.1824
Female		**-0.4074**	**-0.5497**	**-0.5084**	**-0.4472**	**-0.5152**	0.1458

** Bold numbers indicate significance at 95% confidence level (p<0.05)
* Bold number in italics indicate significance at 90% confidence level (p<0.10). Non-bold numbers are not significant at 90%.

Table 2.9B. ***Utility Parameters - Demographics***

Parameter	Nuts	Others	Pop Corn	Pastries	Pretzels	Puffs	Yogurt
Intercept Baseline Utility	-0.3954	**-0.9196**	**-0.8065**	**-0.6751**	**-0.8168**	**-1.4937**	**-1.4675**
Normal Weight	**0.4078**	**0.3427**	0.1032	**0.4001**	0.2811	0.3221	**0.4673**
Obese	0.273	**0.4021**	0.2167	0.2627	0.263	0.3047	0.1968
Age <=18	**-1.584**	0.0014	-0.0947	0.1177	-0.3323	0.409	-0.2558
Age >=65	**0.6219**	***0.329***	0.1171	0.0088	-0.0938	***-0.5228***	**0.6161**
Female	**-0.4065**	0.0151	-0.2442	-0.1635	***-0.32***	***-0.3312***	0.0883

Table 2.9C. ***Utility Parameters - Covariates***

Variable	**Estimate**
Day Dependence – Category	**1.9400**
Time Dependence – Category	0.0957
Day Dependence (Cat)* Log (Delay+1)	**0.3016**
Time Dependence (Cat)* Log (Delay+1)	***-0.1432***
Day Dependence - Brand	**1.6504**

Time Dependence - Brand	**-0.6402**
Fat	**0.1519**
Carbohydrates	**-0.0251**
Fiber	**0.2978**

Table 2.9C. Continued

Protein	**-0.0081**
Before & at Breakfast (BF)	**2.0966**
Between Breakfast & Lunch (BL)	0.2667
Between Lunch and Dinner (LD)	-0.3005
After Dinner (AD)	**-1.1371**
Weekend	-0.089

Table 2.10A. ***Satiation Parameters***

Satiation Parameters	Ice-cream	Cakes	Candy	Chips	Cookies	Crackers	Breakfast Bars
Baseline (Raw)	-0.07350	**1.1451****	0.38	**1.0084**	***0.5232****	0.2933	**0.9162**

Table 2.10B. ***Satiation Parameters***

Satiation Parameters	Nuts	Others	Pop Corn	Pastries	Pretzels	Puffs	Yogurt
Baseline (Raw)	***0.8427***	-0.2324	***2.4588***	**1.999**	0.5514	**1.431**	-0.1032

Table 2.10C. ***Satiation Parameters - Covariates***

Variable	Estimate
Age <=18	**0.4825**
Age >=65	**0.4654**
Female	0.0126
Normal Weight	***-0.2262***
Obese	0.1778
Fat	**0.0216**
Carbohydrates	**0.0196**
Fiber	-0.1603
Protein	***-0.0038***
Before & at Breakfast (BF)	0.2008
Between Breakfast & Lunch (BL)	**0.6900**
Between Lunch and Dinner (LD)	-0.0420
After Dinner (AD)	**-0.5618**
Weekend	-0.0387

2.6 DISCUSSION

In this study, we wanted to examine whether habit or variety seeking was a stronger force driving category choice and quantity choice in the context of snacking. To reconcile past results, we proposed two types of state dependence – time dependence (the effect of prior snack choice on current choice within a day) and day dependence (the effect of snack consumed at a daypart on choice the next day at the same daypart). We tested the impact of both types of state dependence for both category and for brand. We used a variant of the MDCEV model to model both category choice and quantity choice, while capturing multiple discreteness and satiation with quantity. We also estimated the model with controls for unobserved heterogeneity in intercepts and in satiation parameters. The fact that the MDCEV model is derived from random utility maximization theory provides a theoretical grounding for application in our context. This model has not been applied to study variety seeking/habit in prior research.

Our results indicate that, within a day, consumers exhibit variety seeking behavior with respect to brands and to a lesser degree with categories. However, across days at the same daypart, they exhibit strong habitual behavior for both brands and categories. This suggests that managers could associate particular categories of snacks with a daypart to encourage habit formation and make it less likely that consumers would switch categories. The evidence also indicates that consumers do seek brand variety within a day. This suggests that firms need to provide sufficient variety in brands within a snack category. This is consistent with Inman (2001) who uses theory on sensory specific satiety to show that consumers are likely to exhibit greater variety seeking at a flavor level (or on sensory attributes) rather than at a brand level (nonsensory attribute). We leave the examination of variety seeking at a flavor or even texture level as a potential avenue for future research.

The proposed model can be used to assess drivers of choice, quantity, and satiation within a single framework. Specifically, the model suggests two strategic levers: baseline preferences, which are influenced by habit, and satiation. In particular, since satiation measures the rate of decline in consumption with quantity consumed, it governs the quantity of consumption at a given snacking occasion. As our literature review indicates, satiation can be influenced in a variety of ways that might benefit a firm or policy maker. For example, inducing consumers to slow their rate of consumption can lower satiation and increase consumption (Galak, et al. 2012). One way for a firm to slow the rate of consumption and decrease satiation is to limit the availability of a focal item (Sevilla and Redden 2014). A way to limit availability might be to design package or portion sizes that encourage consumption at an optimal (lower) rate. Many other examples could be constructed. The contribution of our research is to provide a model in which changes in satiation might be measured.

Our results for BMI have implications for efforts to reduce obesity. While the choice of snacks does not vary much with obesity, we found that obesity is associated with low satiation, i.e., obese consumers tend to reduce their rate of consumption less than others. Therefore, a worthy policy goal would be to increase the rate of satiation of obese customers. Age (young and old) was also associated with low satiation, and the policy implications would be similar to those for obesity. We also found that satiation is lower in the morning and higher after dinner. Morning hunger may allow individuals to consume more calories of snacks during this daypart relative to other dayparts. This allows us to conduct a thought experiment. If consumption of a snack were to be shifted after dinner to afternoon, our model implies that the calories consumed would be higher. For instance, one can compute the difference in calorie consumption if ice cream were consumed in the afternoon instead of after dinner. On the other hand, if the goal is to reduce consumption, snacks may be shifted to a more beneficial daypart. The model permits such calculation for each snack and each segment.

2.7 CONCLUSION

Although a large body of literature is available in marketing describing the purchase behavior of households using scanner panel data, little is known about how individual consumers behave and make decisions with respect to consumption. The absence of an easy to estimate model to describe simultaneous consumption of products, and to model both choice and quantity has impeded our understanding of consumer consumption especially of food and entertainment options (movies, TV shows, and games). Through our application of MDCEV model, we are able to contribute to the literature by being the first to delineate baseline utility and satiation levels of distinct snack categories and also account for multiple types of state dependence in consumption. While snacks have become the fourth meal, they have not been studied extensively. We are not aware of another study of category choice, habit, variety seeking, and satiation for snacks.

We discuss the results and their implications at length in the sections above and the insights obtained have implications for both managers and policy makers. To get additional insights, it is possible to construct simulations based on our results. For example, one can simulate the effects of switching categories of snacks across dayparts to either increase or decrease calorie consumption. One can also simulate the effects of switching categories (e.g., consuming nuts/seeds instead of cookies) on calorie consumption.

The proposed model has a few limitations. Bhat (2008) MDCEV model assumes that the utility of consumption of a snack category is additively separable and the error terms follow an extreme value distribution. This model implicitly forces different snack categories to be substitutes that compete for the allocation of calories and does not account for possible complementary relations between snack categories. This is similar to the IIA limitation associated with multinomial logit models. Since consumers tend to consume one snack at a given occasion, the assumptions are reasonable for our data, and lead to simplified computations. Future research can address this limitation by allowing for correlation across multiple categories of snacks by using a normal distribution for the error terms as in Kim et al. (2002). Their probit model is difficult to estimate with many categories as the number of pairwise correlation parameters would increase substantially. In our study, we had 14 categories of snacks.

A possible limitation deals with bias in reporting when customers feel they are being observed. This applies to all diary panel data and self-reported data and our data may also be subject to such errors. In our defense, the data was collected by a professional market research firm for a large company. We believe that such errors are kept to a minimum. We focused on category choice and quantity, unlike past scanner data papers that modeled brand choice. This is due to a practical problem in estimation of MDCEV models with a large number of brands. In our data we have about 500 brands in 14 categories. Estimating a brand choice model is computationally burdensome. Future research may employ estimation methods that can deal with such a large number of choices.

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CHAPTER 3

MODELING CONSIDERATION SETS IN MDCEV MODEL OF SNACK CONSUMPTION: A MACHINE LEARNING APPROACH

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Abstract

We propose a new framework for modeling consideration sets in a multiple discrete-continuous extreme value choice model. This, our proposed framework integrates two streams of literature: 1) multiple-discrete continuous choice models (MDCEV) and 2) consideration sets. The proposed model works in two stages, the first stage consisting of consideration set formation and the second stage consisting of the actual choice made by the consumer given the consideration set. A novel feature of the proposed model is to use an ensemble method called gradient boosting algorithm from the machine learning literature (XGBoost) to predict alternatives in a consideration set at each daypart. We propose that a consumer's consideration set for snacks varies across dayparts within a day. Modeling consideration sets in MDCEV models is rare and we study the extent of bias in parameters due to this omission. Our method significantly reduces the enumeration problem encountered in modeling consideration sets with a large number of alternatives.

Using a unique individual-level panel data of snack consumption, we estimate a utility function that depends on individual characteristics, product characteristics, and time of consumption. We then compare it to a model without consideration sets. We use the model to address two substantive counterfactuals – i) how would a change in the time of the day for a given snack affect calorie consumption of individuals, and ii) how would the replacement of a category with another category affect calorie intake. We show that modeling consideration sets significantly improves the model fit by over 50% and reduces bias in parameters. In the counterfactual thought experiment, we show that when ice-cream is consumed in the afternoon instead of at late night (keeping all other snack consumption constant), calorie consumption reduces by an average

of 32%. Similarly, we find that switching out pastries with breakfast bars, one would consume about 27% fewer calories, on average.

Our results have implications for managers interested in creating optimal consumption bundles and for policymakers interested in addressing over-consumption leading to obesity among US consumers.

3.1 Introduction

In the previous chapter, we modeled both choice and quantity of snacks consumed at home for a representative sample of individuals. We employed the multiple discrete continuous extreme value (MDCEV) model proposed by Bhat (2005) to handle multiple discreteness, a phenomenon where consumers may consume multiple snacks in a given time period. The multinomial logit model cannot jointly model choice and quantity and cannot handle multiple discreteness. We also noted that using the MDCEV model allowed us to investigate satiation, habit, and variety seeking behavior in a single framework.

It is well established in the discrete choice model literature that each consumer may not consider all available options and may stick to a set of preferred choices. The phenomenon called choice sets or consideration sets is an important idea and modeling consideration sets has a long tradition in marketing (Manski 1977, Swait and Ben-Akiva 1987a, b; Nierop et al 2010). Research has shown that modeling consumer choice sets in discrete choice models not only improves the model fit considerably, but also reduces bias in parameters. Since choice sets are not observed in practice, a common practice in discrete choice models is to enumerate all possible choice sets and then estimate the discrete choice model conditional on a given choice set. This methodology can handle only a few alternatives as the number of possible choice sets increase quickly with the number of alternatives. For example, for a five-alternative model, there are 2^5-1 = 31 possible choice sets. In our MDCEV model we have 14 categories of snacks and so there are 2^{14}-1 = 16383 possible choice sets. If we were to model choice among the 500 brands in the data, the above method becomes unwieldy.

To simplify the enumeration problem, Bronnenberg et al (2010) suggested that enumeration may be limited to a fewer number of likely candidates. They proposed using a binary probit model to model whether each alternative is likely to be in the choice set. Based on a threshold, they reduce the number of feasible alternatives for a customer from the complete set to a smaller subset of alternatives. They then use enumeration on the smaller subset to obtain the choice model parameters. They apply the model to consumer choice from among 12 brands using scanner data.

Within the MCDEV category of models, there is only one paper (that we are aware of) that models consideration sets (Castro et al 2011). They estimate their model by enumerating all possible choice sets for a small number of alternatives. In our data, we have 14 categories and over 150 brands of snacks. In the spirit of Bronnenberg et al (2010), we suggest use of XG Boost, a machine learning method instead of a multinomial probit model to first reduce the set of alternatives and then use enumeration to obtain parameters of the MDCEV model. We wish to determine how much improvement can be obtained by modeling choice sets in the context of a MDCEV model and to understand habit, variety seeking and satiation in the context of snack consumption.

We then use the consideration set MDCEV model to conduct counterfactual simulations to answer important questions related to snacking. By how much would the number of calories consumed change, if an individual is offered a high-protein breakfast bar instead of a high-carb pastry? What if the individual is asked to change his time of consumption from late-night (post-dinner) to an earlier part of the day? What if both these options are exercised at the same time? Would there be an overall increase or decrease in calories consumed? We build on research in the areas of obesity, nutrition, and diet, and we find that changes in the time of the day, the type of snack consumed or a combination of both (time and snack) do have a significant impact on the overall number of calories consumed by individuals. Using a rich panel data, we calibrate a model that captures an individual's choice of snack(s) and calories simultaneously and discuss the implications for managers and policymakers.

We make five main contributions through this article. First, we integrate two streams of literature – namely consideration sets and a multiple-discrete continuous class of models in one unified framework that is consistent with the Manski (1977) framework. Second, we integrate literature from machine learning (XGBoost) and ease computational burden of enumeration of consideration sets (in data with many alternatives) consistent with Swait (1984, 1987) and Nierop et al. (2010). By modeling consideration sets in MDCEV models, we achieve significant gains in model fit and reduce bias in parameters as in Li, Adamowicz and Swait (2015). Third, we use the improved MDCEV model to underline factors that affect habit, variety seeking and satiation in snack category choice made by individuals. The model can handle multiple-discreteness, discrete choice of category and calories consumed. Fourth, we outline the role played by time of the day on calories consumed by individuals and on satiation. Finally, using counterfactual simulations, we show that there is a significant change in calorie intake when the time of consumption of a given snack is changed. The model can also be used to study the effect of substitution of one snack for another after accounting for satiation. The model has application for firms and policy makers who focus on reducing obesity.

In order to answer these questions, we need to capture data on at-home consumption of snacks and factors affecting the choices made by consumers. Factors such as individual characteristics, product characteristics, consumption context or circumstances, needs of the individuals, activities, and moods of the individual affect consumer choice of category and quantity consumed.

Working with a large snacking business, we were able to access a unique consumption data of 341 randomly selected participants. By calibrating this data on the proposed empirical model, we study the various factors that affect the choices made by consumers at home. The proposed model consists of two-stages - consideration stage and choice stage - in which individuals choose from a set of alternatives. Using the choice of alternative and choice of quantity, and the framework of Manski (1977), we extend the multiple-discrete continuous class of choice models (Bhat, 2008) by adding the consideration phase as in Swait (1984), Swait and Ben-Akiva (1987a, b). Based on prior literature, enumeration techniques were used to model the consideration phase, which involves estimating parameters over a large number of potential consideration sets (more than 16,000 in our setting). In order to ease the computational burden, we use a new machine learning model (extreme gradient boosting) to predict consideration sets based on observed choices (Nierop et al. 2010). This method allows us to estimate the proposed model without having to enumerate over every possible consideration set. In the second stage, we use the multiple discrete-continuous framework, where the consumer chooses multiple goods and quantities on an occasion. For robustness checks, we also estimate a model without the consideration stage, and another model with random intercepts. The model of consideration sets in the first stage and multiple-discrete continuous choices in the second stage, is compared to these two models (we don't find much improvement with the random intercepts). We find that the proposed model provides a good fit for the consumption behavior of consumers for each alternative. The parameter estimates provide evidence of both observed and unobserved heterogeneity in the context of multiple-discrete continuous consumption. We show that demographics can be used to show the differences in preference over alternatives and the differences in quantity consumed on each occasion. We find that the estimated parameters are consistent with prior research and theoretical expectations. Since the model is based on random utility maximization theory, the estimates can be used to conduct counterfactual simulations and measure changes in consumer welfare for a change in the consumption context. Hicksian compensating variation (Dubé 2004) is used to measure the change in quantity consumed to maintain the utility level for a change in consumption context (time or category). Thus, our model, through the intuitively derived estimation function has both empirical and practical implications. Under two counterfactual simulations, we show that consumption of calories changes (increased or decreased) when the time of consumption is changed, or a category is replaced with another category. These counterfactuals show a change of about 18%-20% consumption in calories for a given instance. Our results have implications for both managers and policymakers who are concerned with consumer welfare. Managers can re-position snacks for a different time of the day to encourage consumption, while policymakers can use this information to encourage change in time of consumption or category removal to discourage consumption. The results can also help firms design optimal package sizes and bundles such that consumers satiate slower and thus increase overall consumption.

We organize the paper as follows. In section 2, we discuss the different areas of literature we draw our model from and outline the contributions we make. We discuss the model and the estimation procedure in section 3. Section 4 gives an overview of the data and the methodology we use to arrive at our key variables. Following that, in section 5 the results are discussed with a focus on key estimates that outline the need for our methodology. We report counterfactual simulations of the proposed model to various changes in the consumption conditions. We conclude in section 7 with an overview of the implications of our research and limitations.

3.2 Literature

3.2.1 Obesity and Snacking

Obesity is one of the main health concerns facing policymakers, governments across the globe. In 1988, the World Health Organization (WHO) declared obesity as a public health epidemic. WHO defined obesity as abnormal or excessive fat accumulation that may impair health (Camacho and Ruppel 2017) and net-positive energy intake (more energy consumed than expended) is the fundamental cause of obesity and excess weight (WHO 2015). Primarily, an increase in consumption of snacks, defined as eating occasions different from main meals (breakfast, lunch, dinner) has been found to be one of the contributing factors for excess weight (Forslund et al. 2005). Behaviors such as late-night consumption of snacks, greater intake of high-calorie snacks were cited to be associated with greater energy imbalance, resulting in an increase of overweight and obese individuals (Piernas and Popkin 2010) over the last 5 decades. Policymakers addressing the obesity epidemic suggest either increasing calories expended (exercises or physical activities) or decreasing calories consumed through diet plans or through reduced consumption of ingredients such as carbohydrates (Camacho and Ruppel 2017). One of the methods suggested to address excess calorie intake is to change consumption patterns – increase or decrease consumption occasions, shifting calorie consumption from a later part of the day to an earlier part of the day, or changing the type of snack consumed (Greenhalgh 2002). For example, switching a bedtime snack to a breakfast cereal may help control excess energy intake and contribute to weight loss (Waller et al. 2002). Further, Waller et al. (2002) find that individuals who are compliant with this switch, consume significantly lesser calories in a day and show a significant reduction in calories consumed post-dinner. They also show a significant reduction in weight over the observation period. As the effects of the push for change in calorie consumption or increase physical activity for addressing the obesity epidemic are being studied, it may be worthwhile to give due consideration to other methods such as switching the time of consumption or category as we hypothesize (and discussed in nutrition literature) given that the changes are minimal and simple to implement. Prior research has shown that managing one's diet is easy in theory but difficult in practice (Waller et al. 2002), especially for those who are actively trying to manage their weight. For such individuals, apart from using other methods such as avoidance of certain types of foods or nutrients (saturated and trans-fat foods), participating in physical activities, simple changes in consumption patterns discussed in this paper can enhance weight loss.

Substantively, our results show that a simple intervention such as switching time of consumption or a snack could help individuals who snack later in the night (post-dinner) to reduce their overall calorie consumption. Treatment of obesity using dietary plans that require a tremendous amount of effort and will-power could be substituted or supported by the minimal changes that we suggest in this paper.

3.2.2 Discrete Choice Models

Marketing scholars and practitioners have studied the effects of various marketing activities on purchase behavior (brand choice) of consumers using store-level (scanner panel data) for the last few decades. Effects of prices, location, loyalty, promotions, prior choices (state), stockpiling on choices made by consumers at the check-out lines or the retail stores have been well-studied over these years. Papers by Bass (1974), Chintagunta, Jain, and Vilcassim (1991), Gönül and Srinivasan (1993), Guadagni and Little (1983), Seetharaman, Ainslie and Chintagunta (1999), Chan, Padmanabhan and Seetharaman (2007) are some of the examples in which effects were studied in detail. The results from these papers and the subsequent works by various authors have provided enough evidence on the roles marketing variables (the 4Ps) play in shaping consumer choices and ultimately the demand for various goods and services that firms produce. In prior research, the demand for products is aggregated over a stream of consumption occasions that are unobserved by researchers (Hendel 1999, Dubé, 2004). Consumption occasions are overlooked in empirical settings and usually assumed away in most papers. The recent paper by Huang, Khawaja, and Sudhir (2015) used intraday beverage consumption data to estimate a model where consumers are assumed to balance their short-term needs (quenching thirst) and long-term goals (health). In all these settings, researchers often make two fundamental assumptions, 1) choice of only one alternative at an occasion and 2) availability of all choices to all individuals.

When estimating consumer demand for products, researchers use choices made by households in scanner panel data (Guadagni and Little 1983) and rely on certain assumptions about how consumers make choices. These models rely on the assumption that consumers choose an item that gives them the most utility. Based on this assumption, the model captures the choice of one item from a portfolio of alternatives (assumed to be perfect substitutes), while ignoring the choice of the quantity that a consumer makes. However, in most purchase occasions, consumers make more than one choice (from a set of imperfect substitutes) and choose more than one unit for each alternative (Dubé, 2004). Dubé (2004) points out that ignoring multi-category and multi-quantity purchases in shopping occasions could lead to incorrect managerial implications and result in estimates that do not capture the whole picture of consumer preferences. Unlike scanner panel data, where shoppers anticipate multiple usage situations, variation in preferences by consumption occasions, and multi-user consumption (multiple household members), in our context, we observe individual-level consumption (alternative and quantity) at an occasion. Therefore, it becomes more important that we include both the choice of snack and the choice of quantity consumed in one unified framework. In order to make useful predictions and draw meaningful inferences about consumer choice behavior, we need a model that can capture both choices of multiple goods and choices of multiple quantities on an occasion. Based on the framework proposed by Hendel (1999), Kim and Allenby (2002), Dubé (2004) and extended by Bhat (2008), we use the multiple-discrete continuous (MDCEV) framework to study the consumption choices of consumers in the context of snacking.

Consumers choose different snacks and varying quantities at different times of the day. But across two days, consumers tend to choose similar items. For example, one could consume pastries for breakfast, chips at lunch, popcorn in the evening and ice-cream as dessert at late night within a day. The next day, one is more likely to consume pastries for breakfast, chips at lunch, etc. This type of consumption pattern could be driven by the accessibility of snacks, the context in which the snack is consumed or a need for variety due to satiation on certain attributes of the products. McAlister (1982) documents individuals seeking variety by switching. In Table

3.1, we summarize the three streams of literature that we contribute to, namely, multiple-discrete continuous (Bhat 2008) class of models, consideration sets in discrete choice models (Manski 1977, Swait 1984, Swait and Akiva 1987) and variety-seeking and habituation (McAlister 1982, Kahn 1995, Seetharaman and Chintagunta 1998).

3.2.3 Consideration Sets

In discrete-choice literature, consideration sets were not included in the empirical models due to the difficulty in identifying them as they are unobserved and latent when using observational data (Ben-Akiva and Boccara 1995). Ignoring the role of consideration sets in the consumer's decision-making process results in biased parameter and welfare estimates (Swait and Ben-Akiva 1985). Consideration sets framework has grown out of the works of Manski (1977), extended by Swait (1984, 1994) and applied in the marketing literature (Malhotra, Peterson, and Kleiser 1999; Manrai and Andrews 1998; Roberts and Lattin 1997). The basic framework for this stream of literature is that consumers 'consider then choose', where the first stage involves forming the consideration set by narrowing down the universal set of alternatives (J) to a smaller set ($K \in J$) and then making a choice in the second stage. From a theoretical perspective, allowing consumers to choose from a limited set of alternatives appeal to the notion of consumers using short cuts to make mundane decisions by minimizing the use of cognitive resources (Swait, Popa and Wang 2016).

The use of consideration sets in marketing literature stemmed from the works of Howard (1963), Howard and Sheth (1969), where the consumer's decisions are driven by limitations on one's memory and cognitive ability. Research in this stream also studied the role of brand accessibility (Alba and Chattopadhyay 1985; Nedungadi 1990). In the context of consumption (as in snacking) researchers point to the categorization theory, where the consumer chooses a subset of alternatives driven by the context of usage (Barsalou 1985, Alba and Hutchinson 1987, Bettman and Sujan 1987, Shocker et. al. 1991). Consideration set has been defined as the set of brands that are brought to the consumer's mind in a consumption occasion Nedungadi (1990). Ratneshwar and Shocker (1991) showed that the content of the consideration set varies according to the context of consumption. By using the context of consumption one can generate more dynamic and realistic consideration sets (Aurier et al. 2000). Belk (1974, 1975) reports that about half of the variation in food selection can be accounted for the usage situation and interaction with other variables (individual). In our setting, where consumers choose snacks, we let the consideration sets vary by the usage context (time of the day), individual and product characteristics. This method is in line with the result discussed by Aurier et al. (2000). The context in the paper by Aurier et al. (2000) is about consideration set size and context of consumption (regular meals, individual vs socialized). We expect that consumption of snacks should also follow a similar pattern, where consumers choose certain snacks at different times of day (context). For example, ice-cream and chips are more likely to be consumed in the latter part of the day, whereas breakfast bars and pastries are usually consumed in the earlier part of the day.

Including the consideration stage into the multiple-discrete continuous framework is not trivial, because consideration sets are usually neither observed nor identifiable with certainty (Ben-Akiva and Boccara 1995). Nierop et al. (2010) discuss the various methods that were employed in the consideration sets literature and define two divergent approaches, 1) stated consideration set approach (Roberts and Lattin 1991, Ben-Akiva and Boccara 1995), where the researcher includes consideration sets provided by the consumer in the empirical model, 2) revealed consideration set approach (Manski 1977, Chiang, Chib, and Narasimhan 1999, Mehta, Rajiv, and Srinivasan 2003), where the researcher identifies the consideration set based on the observed choices of the consumers. Since the consideration sets are latent, models need to probabilistically consider each possible consideration set that can be formed from the universe of alternatives. For J alternatives, there are $(2^J - 1)$ potential choice sets. As J increases, the number of possible consideration sets increases exponentially. The largest number of alternatives in a model of consideration sets so far is 12. In our study we have 14 categories of snacks leading to 16,383 possible combinations over which each choice of an individual is integrated. At such a large value of consideration sets, the estimation procedure becomes computationally infeasible and the likelihood function with the inclusion of consideration sets is no longer well-behaved (Andrews and Srinivasan 1995). To simplify the enumeration process, Nierop et al. (2010) suggest predicting whether an alternative will be in a consumer's consideration set using a multivariate binary probit model. This has the effect of reducing the number of potential alternatives for a consumer and thus simplifies the number of potential choices sets that one needs to consider. In predicting a consideration set for each individual/occasion they use individual, marketing, and product characteristics.

Most of the consideration set models have been developed in a discrete choice context. In the MDCEV models context, there is only one paper that models consideration sets (Castro, Eluru, Bhat and Pendyala 2011). They have a small set of alternatives (five) and enumerate 31 (2^5-1) possible choice sets for each customer choice occasion. In the spirit of Nierop et al (2010) we propose using XGBoost, a machine learning approach to predict whether an alternative is likely to be in the choice set at a given snacking occasion for each individual. This reduces the number of consideration sets to be enumerated.

3.2.4 Gradient Boosting Algorithms

We use a state-of-the-art algorithm called extreme gradient boosting (XGBOOST), proposed by Chen and Guestrin (2016). It is an ensemble method that generates a series of decision trees, such that the misclassification rate is reduced over each iteration of the trees. By using a gradient boosting algorithm, we increase the predictive power significantly relative to a probit model. Unlike Nierop et al. (2010), our focus is not on understanding factors that affect the formation of consideration sets and so we employ a method that has been shown to improve prediction accuracy (Chen and Guestrin 2016). In their paper, Chen and Guestrin (2016) show that XGBOOST outperforms all the existing classification algorithms such as GBM (Generalized Boosted Regression Models), and scikit-learn both in terms of computational ease and predictive accuracy. Across various classification exercises (such as click-through rate prediction, Higgs Boson data etc.), Chen and Guestrin (2016) demonstrate the superiority of XGBOOST. Thus, the proposed algorithm has been thoroughly tested and used across multiple publications in computer science (machine learning and artificial intelligence). We use XGBOOST to predict the alternatives likely to be in a consideration set based on the time of the day, individual characteristics, and product characteristics. In Table 3.1, we list key papers in multiple research areas that are pertinent to our work.

Table 3.1. ***Literature***

Paper	Area	Model
Manski (1977)	Consideration Sets	2-stage consider-then-choose model
Swait (1984)		Includes constraints based on economic, social and cultural factors in the discrete choice framework
Swait and Ben-Akiva (1987)		Parametrized Logit Captivity model
Roberts and Lattin (1991)		Marginal utility of additional brand in a consideration set in a 2-stage framework
Andrews and Srinivasan (1995)		Probabilistic model of consideration sets
Ben-Akiva and Boccara (1995)		A probabilistic model of consideration sets incorporates the effects of perceptions and attitudes
Chiang, Chib and Narasimhan (1999)		Consideration-set brand choice model with heterogeneity
Mehta, Rajiv and Srinivasan (2003)		Structural model of consideration set formation as a result of price search behavior
Nierop, Bronnenberg, Paap, Wedel and Franses (2010)		Unobserved consideration sets using observed choices
Li, Adamowicz and Swait (2015)		Bias in estimates and welfare measures due to choice set misspecification
Swait, Popa and Wang (2016)		Mixture model incorporating contextual information to choice models
Hendel (1999)	Discrete Continuous Choice Models	Estimate demand for computers using a linear utility function
Kim and Allenby (2002)		Demand for variety using yogurt data
Dubé (2004)		Demand for carbonated drinks using a linear utility function
Bhat (2005)		Time allocation across discretionary activities
Bhat (2008)		Vehicle ownership choices based on a new utility function
Luo, Ratchford and Yang (2013)		Time allocation across activities
McAlister (1982)	Habituation and Variety-Seeking	Dynamic satiation on attributes of alternatives based on past consumption
Kahn (1995)		Drivers of variety-seeking due to internal and external factors and uncertainty in future tastes
Seetharaman & Chintagunta (1998)		Model of inertia and variety-seeking using marketing mix variables
Castro, Eluru, Bhat & Pendyala (2011)	Consid. Sets and MDCEV	2-stage choice-set model with MDCEV

3.3 Model and Estimation

3.3.1 Multiple Discrete-Continuous Choice Model

On many occasions, such as shopping at retail stores, financial portfolio selection, automobile ownership, activity participation, time use (Bhat 2005; Bhat 2008) consumers choose multiple items across multiple categories subject to constraints such as income, time, abilities, needs or moods, etc. For example, in a grocery store, a consumer can choose breakfast cereal, yogurt, and lunch entrées, from the set of all brands across categories at a shopping occasion. At the same time, a consumer can purchase multiple units of each item. This phenomenon has been called *multiple discreteness* and has been modeled by Hendel (1999), and Kim and Allenby (2002) and Bhat (2005).

The choice of alternatives is governed by individual preferences and product characteristics and is constrained by the budget or income of the individual making the choice. With regards to the quantity choice, consumers face diminishing marginal utility as the quantity consumed increases, a phenomenon also known as satiation. Traditional discrete choice models such as Logit or Probit assume all alternatives that a consumer faces to be perfect substitutes and structured in a way that they cannot use the information about quantity. They also assume a utility function that results in a constant marginal utility irrespective of the amount of quantity consumed. Bhat (2005, 2008), building on works of Hendel (1999), Kim and Allenby (2002), Dubé (2004) proposed a new class of models known as MDCEV model.

Assuming an additively separable function, the utility from consuming *M* of *J* goods that a consumer chooses can be written as:

$$U(x_1, \dots, x_m, 0, \dots, 0) = \sum_{k=1}^{M} \frac{\gamma_k}{\alpha_k} \; \psi_k(\, k) \left[\left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right] \tag{1}$$

$U(x_1, \dots, x_m)$ is a quasi-concave, increasing, and continuously differentiable function with respect to the consumption quantity of alternatives K. x_j, is a non-zero number that represents the quantity consumed from category *j*, *j* = 1,…, J. $\psi_j(j)$ allows us to identify the baseline utility associated with the choice of alternative *j*. α_j influences the rate of change in the utility (diminishing marginal utility) of consuming alternative *j* and γ_j acts as a translation parameter allowing for zero consumption of any or all of the goods (γ_j= 0, implies consumer chooses a non-zero amount of alternative *j*, $\gamma_j \neq 0$, implies consumer doesn't choose alternative *j*). The values of baseline utility and satiation parameters ($\psi_j(j)$ and α_j) decide the choice of alternative and how much of *j* consumer chooses. The baseline utility function can be parametrized as $\exp(X\beta + \varepsilon_j)$, where X is a vector of covariates and consists of a constant term that captures the average preference for alternative *j* (Bhat, 2005) and β is the corresponding vector of coefficients. ε_j is the idiosyncratic error term impacting preference for an alternative *j* and is assumed to be IID and follows an extreme-value distribution. We use demographic information such as age, income, gender, race, education, height, and weight, etc., along with consumption patterns to define the vector X. In discrete choice models, alternative specific variables and socio-demographic information have been used routinely by researchers to explain preferences for various alternatives consumed (McFadden 1973). In consumer behavior literature, repeat choices were observed to be influenced by socio-demographics (Verplanken et al 2005, Hamermesh 2005, McAlister and Pessemier 1982). To accommodate for repeat consumption behavior, we extend the model proposed by Bhat (2005) by including a state dependence term by individual, time and alternative as follows:

$$\beta_j X = \beta_j + \delta_\beta * S_{ijt} + \theta_\beta * I_i + \xi_{ij} \tag{2}$$

where, β_j captures the average preference for alternative j, δ_β captures the effect of the state of individual *i* at time *t*, S_{ijt} captures the state of individual *i* at time *t* based on prior consumption of alternative j. If an individual chooses alternative j at time *t* and *t-1*, then S_{ijt} takes a value of 1 else it takes a value of 0. I_i is a vector of individual-specific variables (demographics). ξ_{ij} is assumed to be IID extreme value and captures the unobserved effects of individual preferences for alternative j. State dependence (effect of lagged choices), which is individual specific and dynamic in nature captures the effect of the previous choice on the current choice and has been employed widely in marketing literature. The positive sign on the coefficient of state dependence term indicates that the individual is conformity seeking or inertial (Jeuland 1979) and when it is negative, the consumption behavior of individuals is termed variety seeking (McAlister 1982). With this specification, we can capture the effects of demographics and state-dependence over preferences.

The term α_j is defined to take a value between 0 and 1, thus governing the shape of the utility function of alternative j and effecting the marginal utility of consumption. For α_j=1, the model collapses to a multinomial logit model, exhibiting no satiation effects, with a linear utility function. This represents the case of perfect substitutes as discussed by Deaton and Muellbauer (1980). For $0 < \alpha_j < 1$, as quantity chosen of the alternative j increases, marginal utility decreases, as $\alpha_j \sim 1$, the alternative j provides immediate satiation and as $\alpha_j \sim 0$, satiation effect of alternative j increases. For stability of the estimation procedure, the satiation parameter (α_j) can be parametrized to vary across individuals as follows:

$$\alpha_j = \frac{1}{1+\exp(-\phi_{ijt})} \tag{3}$$

Where ϕ_{ijt} represents the average satiation for alternative *j* across the population. Extending the model suggested by Bhat (2005), we parametrize the satiation as follows:

$$\phi_{ijt} = \omega_j + \tau_j * Z \tag{4}$$

where ω_j represents the average satiation for alternative *j* and Z represents individual and product characteristics, with τ_j being the corresponding vector of coefficients. As discussed by Bhat (2005), the translation and satiation parameters, although identifiable theoretically, it is infeasible to separately identify. As suggested by Bhat (2005), we fix the translation parameter for all the alternatives as 1 (γ_j=1 for *j* = 1,…,J). Bhat (2008) discusses several utility function profiles based on the values of satiation and translation parameter. These were classified as γ_j profile (if the utility function is defined solely based on the translation parameter) or α_j profile (if the utility function is defined based on the satiation parameter). Note that the γ_j acts both as a satiation parameter and a translation parameter (makes corner solutions possible).

This model captures the utility derived by individual *i* during the time period defined by *t* from choosing one or all of the alternatives *j=1,…,J*. This form of the multiple-discrete continuous choice model allows us to estimate the satiation parameter by alternative based on demographics and individual consumption dynamics (state dependence).

As is the case with the standard logit models, for identification purposes, we designate one of the alternatives as the base alternative and the utility derived from the rest J-1 alternatives is modeled as relative to the based alternative. Thus equation (1) can be written as:

$$U_{it}(c_{it}) = \sum_{j=2}^{J} \frac{1}{\alpha_j} exp\left(X\beta + \epsilon_j\right)\left\{\left(x_j + 1\right)^{\alpha_j} - 1\right\} \tag{5}$$

In this case, one of the categories is chosen as a base good as equation (1) is used as the basis for estimation. In that case, the utility of an alternative is relative to the utility of the base good that is chosen by the analyst. Following Bhat (2008), we write the probability of observing the consumption of M of J goods as,

$$P(c_1, c_2, \dots, c_m, 0, \dots, 0) = \left[\prod_{i}^{M} \frac{1-\alpha_i}{c_i+1}\right]\left[\sum_{i}^{M} \frac{c_i+1}{1-\alpha_i}\right]\left[\frac{\prod_{i=1}^{M} e^{V_i}}{\left(\sum_{k=1}^{K} e^{V_k}\right)^M}\right](M-1)! \tag{6}$$

where, V_i is the observed component of the utility.

3.3.2 Multiple Discrete-Continuous Choice Model with Unobserved Heterogeneity

Following Spissu et al (2009), we allow the model to accommodate unobserved heterogeneity in individual preferences for alternatives j. The unobserved attributes could be individual attributes such as the preference for sweet or salty foods, health constraints etc. that affect individual choices. The baseline utility function can be updated as:

$$\psi_j(j) = \exp\left(\beta_j + \delta_j * S_{ijt} + \theta_j * I_i + \mu_i' * w_j + \xi_{ijt}\right) \tag{7}$$

where β_j represents the average effect of unobserved variables on the baseline preference for alternative j. I_i represents the vector of demographics which captures the observed inter-individual heterogeneity and θ_j is the corresponding vector of covariates. For capturing the individual-level correlation across unobserved utility components of the alternatives (Spissu et al 2009) we use w_j, a column vector of dimension J, each row of this vector represents an alternative. μ_i is specified as a J dimensional realization from a multivariate normally distributed random vector μ, each element with a variance of ω_l^2 (see Spissu et al, 2009 for a richer discussion). This specification captures heterogeneity across individuals due to unobserved attributes that are uncorrelated across alternatives. The error term in the specification is assumed to be IID extreme value distributed across individuals and is considered to be individual alternative occasion specific. The variance of this term captures the unobserved variance across choice occasions for individual i in the baseline preference for alternative j. The probability of consumption seen in Equation 6 is updated to the following,

$$P(c_1, c_2, \ldots, c_m, 0, \ldots, 0 | \theta_j, \mu_i) = \left[\prod_{i}^{M} \frac{1-\alpha_i}{c_i+1}\right]\left[\sum_{i}^{M} \frac{c_i+1}{1-\alpha_i}\right]\left[\frac{\prod_{i=1}^{M} e^{V_i}}{\left(\sum_{k=1}^{K} e^{V_k}\right)^M}\right](M-1)! \quad (8)$$

3.3.3 Multiple-Discrete Continuous Model with Deterministic Consideration Sets

We estimate four benchmark models as a comparison for the proposed choice-set formation model. We use the consumption data from the first week to generate different consideration sets. The first model is the standard MDCEV model with no consideration sets (Bhat 2008). That is, we assume that all consumers consider all snack categories. The second model uses actual choices made by individuals during the first week to generate potential consideration sets. In this model, all individuals are assumed to choose from the same set of items at all times of the day. This behavior is typically observed in snacking where certain items are consumed during certain times of the day. In the third model, we generate consideration sets based on each individual's observed consumption patterns. These consideration sets vary by individual but are fixed across time of the day. Therefore, if an individual chose ice-cream, breakfast bars, nuts and chips in the first week, we assume that she would consider these four items during any consumption occasion. For the fourth model, we generate consideration sets based on individual consumption pattern by the time of the day. In the first week, if the same individual, consumed breakfast bars during breakfast, whereas chips and nuts between lunch and dinner, and ice-cream at post-dinner, the consideration set would vary by breakfast, lunch and dinner and post-dinner according to the choices made.

Naïve consideration sets based on prior consumption history were discussed in prior research and were called deterministic consideration sets (Andrews and Srinivasan 1995). They argue that naïve consideration sets can be used when the researchers believe that consideration sets are formed based on memory, or in situations where variables that effect consideration set formation are not easy to identify. In our case, we use this as a benchmark to illustrate and compare the model fit of these four models with that of the 'predicted' consideration sets discussed below.

3.3.4 Multiple-Discrete Continuous Model with Probabilistic Consideration Sets

In this section, we discuss the independent availability logit model first proposed by Manski (1977) and discussed by Swait (1984) and Swait (1987). The underlying assumption of this model is that, all the alternatives that are in the consideration set are available to a consumer independent of each other's availability. This assumption is easy to support, and as an example, take the case of shopping for consumer-packaged goods (CPGs). A store makes a large variety of goods available to the consumers, and if a consumer purchases a brand of yogurt, it doesn't mean that another brand of yogurt or another brand in a different category weren't available at the time of purchase. We can only conclude that the consumer preference of the brand was driven by individual tastes and/or marketing actions at the time of purchase. However, this doesn't say anything about other goods within and outside the yogurt category. In our context, we observe the consumer choosing from a set of goods that were at her home. If we assume that all categories are available with all individuals at the time of choice (a difficult assumption to support), a model with the universal choice sets is valid. However, this may not be the case as evident from the model-free evidence we present. We show that most consumers choose from a limited set of alternatives at any given time of the day. Thus, modeling consideration sets is important to uncover true consumption behavior.

The IAL is written as:

$$P(C) = \frac{\prod_{i \in C} D_i \prod_{j \notin C} 1 - D_j}{1 - \prod_{k \in M}(1 - D_k)} \tag{9}$$

Suppressing the notation for individual (n) and time (t), we can write the probability of C being the consideration set P(C) as the product of individual availability probabilities of the choices. Let M be the set of all possible combinations of the alternatives in the universal consideration set, with C being one of the subsets of M from which a consumer chooses an alternative at a given occasion. The denominator in equation (9) precludes the probability of considering a null set. If C is known apriori, as in the memory-recall model of consideration, we don't have any uncertainty about the consideration set, and we can simply use C as the consideration set and estimate the parameters of a model conditional on C. However, when C is unknown, as in most grocery shopping scenarios or consumption choices, we include the choice sets in a probabilistic model that enumerates all possible combinations of the choice sets drawn from M. Given X (a matrix of observed covariates), we can write the probability of a particular alternative being in the choice set as:

$$D_i = \frac{1}{1 + \exp(-X\beta_n - Z\delta_j)} \tag{10}$$

Let $P(i|C)$ be the probability of choosing alternative i, conditional on it being in the consideration set C. Using (9), the unconditional probability of choosing alternative i, can be written as:

$$P(i) = \sum_{c=1}^{C} P(i|C)P(C) \tag{11}$$

Equation (11) is summed over all possible subsets C, giving the probability of choosing alternative i. The log-likelihood function is the product of probabilities across observations and is written as $LL = Log\left(\prod P(i)\right)$. This model requires us to enumerate all possible combinations of the alternatives in the observed data. With k alternatives, one has to enumerate $2^k - 1$ possible choice sets. Various researchers have proposed different ways to deal with this problem. Abaluck and Adams (2016, 2018), following Goeree (2008) propose a sampling method that can ease the computational burden. However, their model is identified based on price variation which we do not have. Using observed purchases, Nierop et al. (2010) suggest using a multivariate binary probit model to predict the probability that an alternative is likely to be in the consideration set for a consumer. Using a threshold value, they reduce the number of items from a large number to a smaller subset. They then enumerate all possible consideration sets for this smaller set.

As an alternative method to Nierop et al (2010), we propose using XGBOOST to predict the alternatives that are likely to be in a consumer's consideration set at a specific daypart. These predictions vary by individual, time of the day and product characteristics. Using these subsets, we move to the first stage of the estimation process, where we use the IAL formula to iterate over a smaller number of possible consideration sets. We believe that XGBOOST will provide greater accuracy in prediction relative to the probit models.

In the first stage of the estimation model, we use six variables that indicate the need for a snack at the time of consumption. Consumers indicate which one of 25 needs statements (e.g., I was bored, I ate this to give me a boost etc.) prompted their snack choice. Using equations (9)-(11), we estimate the probability of choosing an alternative given the predicted choice sets.

3.3.5 Consideration Set Formation

As an extension to the previously discussed models, we assume that the choice of quantity c_i, is made simultaneously with the choice of alternative, conditional on that alternative being in the consideration set C_{int} ($C_{int} = C_{1nt},\ldots,C_{Mnt}$). C_{int} is a vector of 1s and 0s, indicating the presence or absence of an alternative *i* at time *t* in *n*'s consideration set. We denote the universal choice set as U, consisting of all the alternatives that are consumed by the participants in the sample. The chosen alternative is denoted by d_{int}, and we highlight that in our model, at any time *t*, consumer can choose more than one alternative, therefore, the vector of chosen alternatives is represented as $D_{nt} = (d_{i1t}, \ldots, d_{imt}, \ldots, d_{iKt})$. D_{nt} is a vector of 1s (and 0s), representing alternatives that were chosen (and not chosen), by the consumer at time *t*. The vector of consumption quantities is represented by $X_{nt} = (x_{1nt}, \ldots x_{mnt}, x_{m+1,nt}, \ldots, x_{Knt})$.

In our proposed methodology, we infer the consideration set by an individual based on prior choices. In order to do that, we split the consumption data into two parts, the training dataset which is based on the first week's consumption and the remaining data (second week) is designated as the test dataset. The XGBOOST algorithm uses the training dataset to estimate the parameters of the optimized loss function, and the estimated parameters are used to predict the consideration sets for the second week.

We follow the framework proposed by Akiva and Boccara (1995) and predict consideration sets using individual characteristics, product characteristics (fat, protein, fiber, carbohydrates) and situational characteristics (time of the day). As mentioned earlier, we use XGBOOST (gradient boosting) to predict the consideration sets based on the individual characteristics, time of day, product characteristics. Time of the day (dayparts) plays a critical role in building consideration sets as the categories that are chosen by consumers for consumption at vary by times of the day. We see that in our dataset, most choices are related to the time of the day at which they are consumed. For example. breakfast bars and pastries are mostly consumed in the morning, whereas ice cream and candy are mostly consumed post-dinner. In our model, consideration sets vary across individuals and within individuals by the time of the day. And since individuals are looking for different attributes provided by different products (McAlister 1982), we allow the consideration sets to vary by product characteristics as well. For example, in the morning, consumers look for high energy foods (carbohydrates), while in the afternoon they may be consuming food to kill boredom or to tide over hunger till the next meal consumption occasion. Thus, at each consumption occasion, the product attributes sought could vary and thus affect the consideration set. In the consideration set formation phase, we use individual characteristics (X_i), time of the day (P_d) and product characteristics Z_k to predict the alternatives.

The function that the boosting algorithm optimizes is written as,

$$\mathcal{L}^n = \Sigma_{j=1}^{N} l\left(y_{it}, \hat{y}_{it}^{n-1} \quad + f_n(X)\right) + \Omega(f_n) \tag{12}$$

where, *N* is the number of additive functions used to predict the output $\hat{y}_{it}$, X represents the individual characteristics, time of day and product characteristics and written as $g(X_i, P_d, Z_k)$, and is used to identify the consideration sets. $\Omega(f_n)$ represents a function that penalizes the model for complexity. The regularization term is included to avoid over-fitting the model to the data and ensure that the model is valid for prediction on new data points.

Using the predicted alternatives from the XGBOOST algorithm, we move to the next step of estimating the two-stage consideration set and discrete-continuous choice model. Let C_{nt} be the all the consideration sets predicted by the XGBOOST algorithm. In the first stage of consideration set formation, instead of iterating over 2^J-1 possible consideration sets, we iterate over the predicted set C_{nt}. The size of C_{nt} depends upon the number of alterantives chosen by the consumer at a daypart and notice that C_{nt} will always be a subset of the total possible consideration sets based on the universal choice set *U*. The consideration set formation stage is assumed to be dependent upon the context of consumption that drive choices. Using equations (9) and (10), we estimate the probability of each predicted consideration set. The probability of choosing M of J alternatives, conditional on the consideration set is written as follows,

$$\mathrm{P}(\mathrm{c}_1, \mathrm{c}_2, \dots, \mathrm{c}_\mathrm{m}, 0, \dots, 0|\mathrm{C}_\mathrm{it}) = \sum\nolimits_{\forall C_{it}} \mathrm{P}(C_{nt}|\beta) \left[\prod\nolimits_i^M \frac{1-\alpha_i}{c_i+1}\right]\left[\sum\nolimits_i^M \frac{c_i+1}{1-\alpha_i}\right]\left[\frac{\prod_{i=1}^{M\in C_{nt}} e^{V_i}}{\left(\sum_{k=1}^{K\in C_{nt}} e^{V_k}\right)^M}\right](M-1)! \tag{13}$$

The likelihood function is written as $LL = Log\left(\prod \mathrm{P}(\mathrm{c}_1, \mathrm{c}_2, \dots, \mathrm{c}_\mathrm{m}, 0, \dots, 0|\mathrm{C}_\mathrm{it})\right)$.

3.4 Data

The data that we use for this model comes from snacking diaries maintained by a random sample of individual consumers using a mobile device provided by the anonymous snack manufacturer. The mobile device assigns a unique identification number to each participant for recording his/her snacking activity. During the data collection period of two weeks, participants record every snack they consumed. The device is used to collect demographic information such as age, gender, race, region, household size, height, weight, income, race, marital status, education, location, weekend or weekday, holiday or non-holiday, exercise level for a day, the snacking occasion (daypart), what snack was consumed at each occasion, what was the quantity consumed, brand of the snack, date among others details. We divide the day into six dayparts (also time of day), 'At Breakfast', 'Breakfast to Lunch', 'At Lunch', 'Lunch to Dinner', 'At Dinner' and 'Post-Dinner'. We consider snacking at mealtimes (that is 'At Lunch' and 'At Dinner') as the basis for comparison for identifying the effects of persistence of choices over time. The snack manufacturer collects this information every year for internal use. The data we use was collected between 2009-2011, includes about 2000 individuals. We sampled 341 individuals from this data that met two criteria: 1) they should have at least 10 snacking occasions in a two-week period and 2) 95% of their snacking is within the fourteen snack categories selected.

We present summary statistics of demographic variables in Table 2a. Of the 341 individuals sampled, about 55% are male, with 70% of the individuals in the 19-64-year age group. The weight distribution, given by the BMI is about 30% over-weight and 33% obese, so, about 63% of the individuals are either overweight or obese. These numbers are in line with obesity and overweight proportions of the general population among US individuals (NCHS 2017). In Table 2b, we observe that 85% of individuals snacked on one item per occasion while 15% exhibited multiple discreteness. That is, they consumed multiple snacks in a given daypart. The panel data consists of 21,145 snacking occasions with 341 unique individuals over a two-week period. They consumed 602 brands in 14 different categories. We show some representative brands and categories in Table 3.2. The participants also provide information on what their needs were at the time of consumption (e.g., hunger, boredom) and what were they doing (watching TV, working) while consuming a snack.

Participants recorded the quantity of snack consumed which allowed us to get data on nutrients consumed such as fat, fiber, protein, and carbohydrates. We had data on individual characteristics

Table 3.2. ***Snack Categories and Brands***

Category	Brand Names
Breakfast Bars	Kellogg's Nutrigrain Granola Bars Quaker Chewy Regular Granola Bars
Cakes	Entenmann's Coffee Cakes Blue Bird Coffee Cakes
Chips	Baked Lay's Kettle Cooked Lay's
Chocolate Candy	M&M's Chocolate Candy Hershey's Chocolate Candy
Cookies	Chips Ahoy Cookies Entenmann's Cookies
Crackers	Cheez-It Plain Crackers Nabisco Wheat Thins
Ice Cream Gelatin	Blue Bell Frozen Sweet Novelties Blue Bunny Frozen Sweet Novelties
Nuts and Seeds	Blue Diamond Nuts David Nuts
Others	Baken-Ets Pork Rinds Macs Pork Rinds
Pastries	Kellogg's Pop Tart Toaster Pastries Pop-Tarts Pastry Swirls Toaster Pastries
Popcorn	Jiffy Pop Uncooked Act II Microwave Popcorn
Pretzels	Rold Gold Pretzels Snyder's Of Hanover Pretzels
Puffs	Cheetos Crunchy Baked Cheetos
Yogurt	Dannon Yogurt Yoplait Yogurt

such as gender, BMI classification (normal, overweight, obese), age groups (under 19, 19 to 64, 65 and above). In order to assess the effect of prior snack choice on current snack choice, we include four state dependence terms (dummy variables) that capture habit or variety seeking behavior. The dummy variable takes a value of 1, if a category (or brand) was consumed in the previous consumption occasion, otherwise it is 0. The coefficients of these dummy variables are defined as structural state dependence estimates by Heckman (1981), and these parameters capture the effect of past choices on current choices. A positive coefficient is interpreted as evidence of habit or inertia while a negative coefficient is interpreted as evidence of variety seeking. Dubé (2004) also includes product- and brand-specific state dependence terms (called brand loyalty and product loyalty) in their model of multiple discreteness using data on carbonated soft drinks. Further, since we are interested in habit or variety seeking behavior within a day and across days at the same daypart, we create additional state dependence terms. For example, if one consumes cereal for breakfast today, then they are more likely to consume cereal for breakfast again tomorrow. But they are less likely to consume cereal at another consumption occasion on the same day. As suggested in Khare and Inman (2009), we consider two different types of state dependence - i) across different time periods within a day (termed *time dependence*) and ii) across days but at the same time period (termed *day dependence*). We estimate time dependence and day dependence terms for both category and for brand, thus giving us four state dependence estimates.

The loyalty term (state dependence) has been found to be useful in capturing prior behavior's effect on current purchases (myopic, Dubé 2004), and models that include state dependence terms have better model fits and predictive power (Guadagni and Little 1983, Erdem 1996 and Keane 1997). Seetharaman et al. (1999) show that there is a wear-out effect of state dependence as the 'time since prior occasion' increases. For example, after consuming breakfast cereal in the morning, a consumer would not enjoy repeat consumption of cereal for 't' time periods. However, as time increases from immediate to 't', his chances of consuming cereal again increases. This phenomenon is referred to as wear-out effect (Seetharaman et al. 1999). We interact time and day dependence at category level with time delay. As in Seetharaman et al. (1999), we use the log(t+1) form to capture this behavior. Log(t+1) and log(d+1) denote the decay over dayparts (t) and over days (d) respectively.

The snack categories are based on terminology provided by the snack manufacturer and are widely used in the industry and retail businesses. In order to compare consumption among the 14 categories, we use calories consumed in place of quantity consumed. This allows us to directly compare the calorie consumption of chips with ice-cream or cookies. If we use the quantity consumed, for example, 1 oz of chips (smallest packet of Lay's chips) with 1 oz of ice-cream or 1 oz cookies, the actual energy consumed will be drastically different. 1 oz of chips contains about 160 calories, while 1 oz of ice-cream contains anywhere between 39 and 60 calories depending on the manufacturer and ingredients. To be able to predict, compare and suggest substitution between any given categories, we need a standardized scale, thus the use of calories instead of weight makes our model unique, providing results that are useful for policymakers, firms, and individuals.

Based on the quantity consumed at each recorded occasion and the food label information available (Nutrition Facts), we calculated the total calorie intake for each occasion based on equation 14.

$$C_{it} = \sum_{c=1}^{c=C} k_c * S_{ic} \tag{14}$$

*i = 1,..,I (*indexes the individual*),*

c = 1,…,C (be the category consumed at the occasion)

k_c = calorie per serving from category *c*

S_{ic} = quantity consumed (in servings) by customer *i* in category *c*

C_{it} = Total calories consumed at an occasion *t* by participant *i*

The calorie intake was then aggregated at a day-part level for participant and snack consumed. This type of aggregation has been used by Bhat (2005), Bhat (2008), Spissu et al. (2009), Sobhani et al. (2012). Their studies were focused on participation and time use in discretionary activities. As discussed previously, the total calories consumed from each brand at every consumption occasion was calculated for every participant. The fourteen categories in the sample are considered as discretionary consumption options which may or may not be consumed by the participants (Bhat, 2008). The daily consumption of these options by each participant constitutes the panel data that was used for this model. The discrete choice aspect of the model results from whether the calorie intake for a category is zero or not. The continuous component of the model results from the magnitude of the non-zero calorie intake of the inside options that were consumed by the participant (Bhat, 2008). Table 2.2B shows the frequency and average calories consumed per category. Chips, chocolate, and cookies are the snacks most often consumed. Pastries, cakes, and nuts have the highest average calories per consumption.

We provide a summary of category choices by the time of the day in Table 3.3. Notice that there are certain foods that are consumed at certain times of the day. For example, breakfast bars and pastries/donuts/muffins are mostly consumed in the morning (at breakfast), whereas, ice-cream, popcorn, and chocolate etc. are mostly consumed after dinner.

In Table 3.4, we provide a summary of calorie consumption by time of the day across each category. Of the 100 calories consumed at breakfast, 36% come from pastries, followed by breakfast bars. Similarly, chocolates provide the most calories during late-night consumption. Even though popcorn is consumed during late night, the calories provided by popcorn is very little overall, compared to the rest of the categories.

Table 3.3. ***Category choice by the time of day***

Category	At Breakfast	Between Breakfast and Lunch	At Lunch	Between Lunch and Dinner	At Dinner	Post Dinner
	Time of the Day					
Breakfast Bars	19%	9%	3%	4%	2%	3%
Cake	3%	3%	2%	2%	2%	3%
Candy	3%	10%	5%	14%	8%	15%
Chips	4%	13%	37%	17%	30%	13%
Cookies	7%	10%	7%	10%	8%	11%
Crackers	6%	8%	11%	9%	10%	6%
Icecream	1%	3%	3%	4%	4%	10%
Nuts	6%	9%	4%	11%	6%	8%
Others	9%	7%	9%	8%	13%	7%
Popcorn	1%	4%	4%	6%	4%	12%
Pastries	29%	10%	4%	5%	4%	4%
Pretzels	1%	4%	3%	5%	4%	5%
Puffs	1%	4%	5%	4%	4%	3%
Yogurt	9%	5%	4%	2%	2%	2%

Table 3.4. ***Calories consumed by category and time of day***

Category	At Breakfast	Between Breakfast and Lunch	At Lunch	Between Lunch and Dinner	At Dinner	Post Dinner
	Time of the Day					
Breakfast Bars	12%	7%	3%	3%	2%	2%
Cake	5%	4%	2%	4%	6%	5%
Candy	4%	12%	6%	18%	16%	19%
Chips	3%	10%	37%	14%	26%	10%
Cookies	6%	9%	10%	9%	8%	13%
Crackers	3%	5%	9%	6%	4%	5%
Icecream	1%	3%	3%	5%	3%	11%
Nuts	10%	11%	5%	15%	6%	9%
Others	11%	8%	8%	8%	14%	7%
Popcorn	1%	4%	2%	3%	2%	6%
Pastries	36%	13%	3%	6%	3%	6%
Pretzels	1%	6%	3%	5%	5%	4%
Puffs	1%	3%	5%	3%	3%	2%
Yogurt	7%	5%	6%	2%	2%	2%

In order to control for the macronutrient profile of each food consumed, we use the nutrient label information and add up the four nutrients that are most commonly found in snacks. Carbohydrates, fat, fiber and protein are measured in grams and are included in our analysis to ensure that we account for satiation effects of the nutrient profile. Prior studies have shown that different nutrients have different effects on satiation (the feeling of fullness at the end of a meal) and satiety (the attractiveness of another meal at some time after the previous meal). We expect to find similar results for our ingredient controls. The summary of ingredients by category is provided in Table 3.5.

Table 3.5. ***Product Characteristics by Category***

	Macronutrients			
	Fat (g)	Carbohydrates (g)	Fiber (g)	Protein (g)
Breakfast Bars	4.09	23.06	1.96	3.08
Cake	9.12	26.71	0.51	1.7
Candy	7.59	21.25	0.42	2.15
Chips	7.36	18.95	1.38	2.13
Cookies	6.8	21.51	0.71	1.72
Crackers	5.77	17.47	0.91	2.73
Icecream	3.82	21.16	0.88	2.49
Nuts	13.91	8.3	2.59	6.24
Others	7.78	19.39	1.14	6.37
Popcorn	6.1	20.04	3.69	2.9
Pastries	8.88	33.01	0.95	3.38
Pretzels	2.48	29.56	1.2	3.92
Puffs	9.16	14.83	0.61	1.9
Yogurt	1.37	22.15	0.36	5.2

3.4.1 Variables for Consideration Set Enumeration Stage

In prior papers on consideration set formation, researchers assume it is influenced by marketing-mix variables (Andrews & Srinivasan, 1995; Bronnenberg & Vanhonacker, 1996). Others have used past purchases as a variable that effects consideration set formation (Siddarth, Bucklin & Morris, 1995). Our context of consideration set formation is slightly different from prior research since it is not based on purchases in grocery stores. The consumers in our panel record their consumptions as they eat a snack at home. We believe that marketing mix variables would have very little role to play since consumers are deciding between two snacks from their pantry, which has been presumably filled earlier. Further, if someone else were to shop for the entire family, then individual members are less likely to consider prices or promotions in deciding their consideration set.

Instead, we use information on needs reported by the consumer at the time of selection of the snack. Ratneshwar and Shocker (1991) use a snacking context to show that usage context and contextual factors affect how consumers recall different snack categories. They justify the results by stating that consideration of a set of products could be driven by their usage context, which could vary based on the needs and goals of the consumers. In our data, participants tick off one out of a 25 item list of needs that describe the reason for choosing a snack. We conduct a factor analysis of the 25 needs and obtain six factors that best describe the dimensions of usage contexts. A consumer would choose a snack because it is 1) her favorite 2) good for her health 3) good to consume in groups 4) good for relaxing 5) for avoiding boredom or 6) to give her a boost.

Table 3.6 shows the percentage of times different snacks were consumed based on the consumption context. Cake is consumed mostly when someone is ‘bored’. And chips are associated most contexts except with the ‘health’ and ‘boost’. Breakfast bars and nuts are usually considered when a consumer needs a ‘boost’ or ‘health’, while yogurt mostly appears when the context is for ‘health’. Note that the usage context and category are not mutually exclusive, that is one category can appear in different usage contexts (yogurt can appear under ‘boost’ or ‘favorite’).

Table 3.6. ***Category and Consumption Context***

Category	Boost	Bored	Favourite	Groups	Healthy	Relax
Breakfast Bars	9%	3%	3%	2%	12%	3%
Cake	3%	6%	3%	4%	1%	3%
Candy	10%	18%	16%	17%	2%	15%
Chips	12%	20%	18%	16%	10%	17%
Cookies	10%	11%	9%	11%	4%	11%
Crackers	10%	4%	6%	5%	8%	5%
Icecream	6%	5%	9%	8%	4%	8%
Nuts	11%	7%	7%	9%	17%	9%
Others	9%	10%	9%	6%	14%	7%
Popcorn	2%	4%	4%	5%	2%	5%
Pastries	8%	7%	7%	7%	7%	5%
Pretzels	4%	3%	4%	4%	4%	5%
Puffs	1%	3%	2%	4%	1%	3%
Yogurt	5%	0%	4%	2%	16%	3%

3.5 Results

3.5.1 Model Fit

In Table 3.7, we show how well our proposed MDCEV model with XGBoost predicted consideration sets fits compared to a baseline model with no modeling of consideration sets and several alternate choice-set models that are based on the first week’s observed consumption patterns of individuals. For the latter, we use the consideration sets derived from choice data in the first week to fit the MDCEV model on the second week data. In all models the first week data is not used for estimation of the MDCEV model.

We find that our proposed model based on predicted choice-sets from XGBoost and probabilistic enumeration of choice sets provides substantial improvement in model fits, based on the values of log-likelihood, AIC, and BIC. The baseline model with no consideration sets has a log-likelihood of -9491.6 while our proposed model has a log-likelihood of -4019.1, indicating a 58% improvement over the base model. The AIC and BIC values, that account for number of parameters and number of observations in assessing model fit, also support the finding of substantial improvement in model fit. In model 2, we assume that consideration sets are governed by the daypart and are same for all consumers. We define consideration set as all the snacks consumed in a daypart (by all consumers) during the first week. We see that using this definition of consideration set improves the log-likelihood value by 1902.7. In model 3, we define an alternate consideration set as the set of all items consumed by an individual in week 1, irrespective of the daypart. This further improves the log-likelihood by another 1000 points. This is expected since heterogeneity in choice sets across individuals is now accounted for. In model 4, we define consideration set as all items consumed by an individual at a specific daypart in the previous week. This yields a log-likelihood of -5463, an improvement of 42% over the base model. So, using naïve observed consideration sets in MDCEV models also improves the model fit considerably. Our proposed model improves on all the naïve CS models. We also wish to point out that incorporating random intercepts in the baseline utility and in the satiation intercepts to control for unobserved heterogeneity yields a modest 5% improvement in log-likelihood relative to the base MDCEV model. Thus, the evidence suggests that modeling consideration sets may be more critical than modeling unobserved heterogeneity using random effects, at least in our context. An alternate explanation of the results could be that modeling consideration sets at an individual and daypart level captures unobserved heterogeneity very well.

Table 3.7. ***Choice sets based on 1st week's choices for Second Week's Data***

Models - 2nd Week data	N	Parameters	Log-Likelihood	AIC	BIC
1. Common Choice Set (Universal) for All Individuals	3565	121	-9491.6	19225.2	19972.8
2. Choice-Set Varies by Daypart	3565	116	-7588.9	15409.9	16167.4
3. Choice-Set Varies by Individual	3565	121	-6587.6	13417.2	14165.8
4. Choice-Set Varies by Individual and Daypart	3565	121	-5463.1	11168.2	11915.8
5. Choice-Set predicted (by XGBoost) Individual and Daypart with CS Formation Model	3565	219	**-4019.1**	**8476.2**	**9829.4**

3.5.2 Estimates for MDCEV Model

We begin with a discussion of our base model. We present parameters for utility and for satiation separately for ease of exposition. The results for the utility specification are presented in Table 3.8A. Note the parameters for the ice-cream category are not estimated in the choice model, as it is set as the base good for identification. Since one of our goals is to understand habit and variety seeking behavior, we begin by looking at Table 3.8C. We observe that both category and day dependence parameters are positive and suggest significant habitual behavior across days for a given daypart. However, within a day, the brand time dependence parameter shows a negative sign, indicating variety-seeking in choice of brands within a day. The sign of category time dependence parameter is not significant. The results indicate that there is brand level variety seeking behavior in snack choices within a day but habitual behavior across days for both category and brand. Our findings are consistent with Dubé (2004), who find that consumers are more loyal to the category than to brands.

In Table 3.8A and Table 3.8B, the baseline intercepts for 13 categories can be interpreted as the intrinsic preference for a snack category relative to ice-cream at zero consumption. We see that chips, cookies, and crackers are preferred over ice-cream, whereas the preference for categories such as chocolate/candy, popcorn, nuts/seeds and yogurt is no different than that for ice-cream. Consistent with well documented research on the effect of demographics on preference for snacks, we find evidence of varying preferences for snack categories by age, gender, and obesity groups. Younger consumers (those under 19 years), have lower preferences for cakes, chips, and others (largely meat-based snacks) relative to the adult group (19-65) years. Similarly, the older age groups (above 65), are similar to adults in most categories except that they show a slight preference for yogurt and 'other' snacks. Females have a higher preference for

Table 3.8A. ***Baseline MDCEV Model Results***

Parameter	Icecream	Cakes	Candy	Chips	Cookies	Crackers	Breakfast Bars
Baseline		**0.392**	1.461	**1.19**	**1.063**	**0.801**	***0.157***
Normal Weight		**0.270**	0.398	**0.537**	**0.431**	**0.379**	***0.379***
Obese		-0.453	***0.181***	0.457	**0.295**	***0.214***	0.644
Age <=18		**-0.024**	-0.947	**-0.317**	-0.426	-0.323	0.021
Age >=65		-0.236	-0.134	-0.315	-0.156	0.083	0.000
Female		**-0.236**	-0.487	**-0.461**	**-0.305**	-0.394	**0.094**

Table 3.8B. ***Baseline MDCEV Model Results - Demographics***

Parameter	Nuts	Others	Pop Corn	Pastries	Pretzels	Puffs	Yogurt
Baseline	0.830	**0.500**	0.589	***0.699***	***0.502***	-0.092	-0.083
Normal Weight	***0.446***	**0.418**	**-0.022**	0.28	0.361	0.309	0.475
Obese	**0.378**	***0.503***	**0.228**	0.182	0.253	0.433	0.184
Age <=18	-1.852	**-0.072**	-0.194	0.181	-0.486	0.466	-0.224
Age >=65	0.488	**0.093**	-0.07	-0.275	-0.307	-0.554	***0.572***
Female	-0.286	0.152	-0.129	-0.052	-0.174	-0.391	***0.321***

breakfast bars and yogurt (relative to ice-creams) and a lower preference for cakes, chips, cookies than males. Normal weight and obese consumers seem to prefer most categories over ice-cream and over-weight consumers. Only popcorn seems to be less preferred compared to ice-cream for, normal-weight consumers. One aspect we need to note is that these effects are for the choices alone.

Table 3.8C. ***Baseline MDCEV Model Results - Covariates***

Variable	**Estimate**
Day Dependence – Category	**2.054**
Time Dependence – Category	***0.278***
Day Dependence (Cat)* Log (Delay+1)	-0.049
Time Dependence (Cat)* Log (Delay+1)	***0.113***
Day Dependence - Brand	**1.226**
Time Dependence - Brand	**-0.87**
Fat	**0.844**
Carbohydrates	**-0.671**
Fiber	**0.919**
Protein	**-0.586**
At Breakfast	**1.95**
Breakfast to Lunch	0.254
Lunch to Dinner	-0.265
Post Dinner	**-1.236**
Weekend	-0.146

In Table 3.8C, foods with fat and fiber are preferred more, while those with carbohydrates and proteins are preferred less. Most consumption choices are made in the morning (before and at breakfast) compared to the base (lunch and dinner). The preferences over snacks at other parts of the day are not different from that of the base, whereas the late-night snacking is less compared to lunch and dinner snacking.

In Tables 3.9A and 3.9B, since satiation is based on calories consumed, we can identify the satiation parameter for the ice-cream category. The intercepts in the satiation model capture relative satiation levels of different snack categories. A high value of the parameter indicates a lower satiation (that is, higher consumption of calories) and vice-versa. We observe that cakes and chips indicate low satiation corresponding to greater consumption. Ice-cream, yogurt and other snacks indicate higher satiation.

In Table 3.9C, we assess the effect of demographics, daypart and nutrients on satiation. Note that the reported estimates need to be reparametrized using equation 3 to get correct differences in magnitude. We see that satiation varies over age groups, gender, and weight categories. Both older and younger individuals have lower satiation relative to the adult group. That is, these groups tend to consume more calories in snacks relative to adults. Females have higher satiation levels relative to males, on average. We find that relative to overweight and obese individuals, normal weight individuals have a higher satiation level. So, evidence suggests that females and normal weight individuals consume lower amount of calories in snacks.

With respect to nutrients, we find that snacks with more carbohydrates and proteins are less satiating (i.e., are consumed more), while foods with fiber are more satiating (or consumed less). Fat content in snacks does not appear to affect satiation levels.

Coming to the effects of time of consumption on satiation, we find that during the early part of the day, individuals have lower satiation and consume more, while later in the day, directionally, they have higher satiation and consume less relative to snacking at mealtimes (lunch and dinner).

Table 3.9A. ***Baseline MDCEV Model Results – Satiation***

Parameter	Ice-cream Gelatin	Cakes	Chocolate Candy	Chips	Cookies	Crackers	Breakfast Bars
Baseline	**-1.26**	***1.074***	-0.570	**0.888**	-0.083	***-0.635***	-0.078

Table 3.9B. ***Baseline MDCEV Model Results – Satiation***

Parameter	Nuts and Seeds	Others	Pop Corn	Pastries Donuts and Muffins	Pretzels and Snack Mixes	Puffs	Yogurt
Baseline	0.613	**-1.036**	8.597	0.677	-0.184	1.13	**-1.213**

Table 3.9C. ***Baseline MDCEV Model Results– Satiation Covariates***

Variable	***Estimate***
Normal Weight	**-0.225**
Obese	0.117
Age <=18	***0.508***
Age >=65	**0.394**
Female	**-0.007**
Fat	-0.139
Carbohydrates	**0.482**
Fiber	**-1.062**
Protein	**0.559**
At Breakfast	***0.413***
Breakfast to Lunch	**0.577**
Lunch to Dinner	-0.022
Post Dinner	-0.263
Weekend	-0.084

3.5.3 Estimates for MDCEV Model with Consideration Sets

Our proposed model is based on predicted consideration sets that are predicted in two steps. First we use XGBoost on a set of observed variables and consumption patterns of consumers in week 1 to predict likelihood of a snack category being in the consideration set. Using a cutoff value, we retain a subset of snack categories and estimate the probability of a consideration set for every possible combination of alternatives in the subset. Using these consideration sets we estimate the MDCEV model.

In Table 3.10, we highlight the important variables that the model uses to predict consideration sets for an individual. For each snack category, the nutrients in the snack (fat, fiber, protein, and carbohydrates), the choice of category and brand made in the previous day (day dependence), the lag between consumption occasions, and the daypart play a key role in predicting whether the product is in the consideration set or not.

Table 3.10. ***XGBOOST - Key Variables used for Predicting Consideration Sets***

Key Variables
Day Dependence (Category)
Fat
Fiber
Carbohydrates
Protein
Day Dependence (Brand)
Time of the Day
Day Dependence (Category)*Log(t+1)

The prediction accuracy on the training sample is about 96%. This is one of the attractive features of tree boosting algorithms, which use a series of weak learners to achieve high prediction accuracy (Chen and Guestrin 2016). The weights of the key variables that are shown in Table 3.10 are then used to predict the consideration set in the second week's data. In some cases, the predictions might result in a null consideration set. In order to overcome this behavior, we let the model choose the alternative that has the highest prediction probability (see Nierop et al. 2010). This ensures that the model doesn't return null consideration sets and there is at least 1 alternative in the predicted set.

We use maximum likelihood estimation procedures to estimate the parameters based on the likelihood function in Equation (13). We report estimated parameters in Tables 11, 12 & 13. In Table 3.11, we show the estimates for the first stage or consideration set formation stage. In Tables 3.12A-C and 3.13A-C we report estimate of the utility function and the satiation parameters respectively.

In Table 3.11, we assumed that consideration set was formed based on needs of an individual at the time of consumption. We identified six groups of needs based on a factor analysis of 25 stated needs. For example, those who state their snack choice is driven by a need for energy boost ("to give me a boost") are likely to prefer candy, breakfast bars, and yogurt in the consideration set. Similarly, consideration sets based on a need for healthy items are likely to have breakfast bars and yogurt. Those who are looking for healthy snacks, are more likely to consider yogurt and breakfast bars and less likely to consider puffs, cakes, cookies etc.. While those are snacking while 'Bored', are more likely to consider cakes, candy, chips, cookies, popcorn and pretzels, while they are less likely to consider ice-cream, nuts, pastries and yogurt. Ratneshwar and Shocker (1991) find that consumers are more likely to choose items such as pizza, popcorn, chips and pretzels in a context of consumption with friends on a Friday party.

Table 3.11. ***Model Results for P(C) - Consideration Set Formation***

Parameter	Ice-cream	Cakes	Candy	Chips	Cookies	Crackers	BF Bars
Baseline	0.142	**0.199**	**-0.885**	**0.717**	0.426	**0.764**	**0.386**
Favorite	**-0.010**	-0.046	**1.116**	**-0.437**	-0.223	-0.728	**-0.495**
Healthy	**-0.469**	**-2.177**	**-1.236**	**-1.587**	**-1.768**	**-1.676**	**0.122**
Groups	**-0.030**	**-0.182**	**1.304**	**-0.591**	**-0.367**	**-0.972**	**-0.878**
Relax	**0.145**	**-0.392**	**1.295**	**-0.294**	-0.103	**-0.626**	**-0.787**
Bored	**-0.074**	**1.023**	**1.920**	**0.674**	**0.357**	-0.197	-0.156
Boost	**-0.390**	**-0.716**	**0.967**	**-0.984**	**-0.328**	**-0.715**	**0.622**

Table 3.11. ***Continued***

Parameter	Nuts	Others	Pop Corn	Pastries	Pretzels	Puffs	Yogurt
Baseline	**0.754**	**0.952**	**-0.239**	**0.372**	0.071	**-0.178**	0.959
Favorite	**-0.759**	-1.238	**0.133**	0.003	**0.261**	0.060	**-0.757**
Healthy	**-0.872**	**-1.284**	-0.932	**-0.644**	**-1.119**	**-6.407**	**0.002**
Groups	**-0.639**	**-1.233**	**0.254**	**-0.369**	**-0.287**	0.007	**-1.176**
Relax	**-0.313**	**-0.968**	**0.750**	-0.007	**0.477**	-0.003	-0.474
Bored	**-0.120**	0.005	**1.337**	**-0.092**	**0.199**	0.679	**-1.023**
Boost	-0.222	**-1.215**	-0.183	**-0.194**	**-0.201**	-0.562	**0.138**

We find that candy and popcorn are more likely to be considered when the usage context is "sharing with groups". Snacking to "relax" are associated with candy, popcorn, pretzels and icecream categories.

Further, from Table 3.12C, the key variables of interest are the four state dependence terms. We now find that consumers exhibit habitual behavior at a daypart across days but exhibit variety seeking behavior in both brand and category within a day. Unlike in the base MDCEV model results (Table 3.8C), we note that the category time dependence parameter is now significant and negative. This reversal of earlier result validates the use of consideration sets in MDCEV models as it helps reduce bias in parameters (Li, Adamowicz and Swait 2015). This is

Table 3.12A. ***MDCEV Model Utility - Demographics***

Parameter	Ice-cream	Cakes	Candy	Chips	Cookies	Crackers	Break-fast Bars
Baseline		-0.713	**0.178**	0.227	0.899	**-0.431**	**0.814**
Normal Weight		**0.675**	**-0.051**	**-0.019**	**-1.049**	0.181	**-1.222**
Obese		0.318	-0.753	**-0.501**	**-1.416**	-0.249	**-0.380**
Age <= 18		-0.511	-0.963	-0.747	**-0.575**	-0.336	**0.121**
Age >= 65		**-2.004**	-0.725	**-0.401**	**-0.396**	-0.097	**-0.072**
Female		0.155	0.050	0.262	**0.580**	0.297	-0.419

Table 3.12B. ***MDCEV Model Utility - Demographics***

Parameter	Nuts	Others	Pop Corn	Pastries	Pretzels	Puffs	Yogurt
Baseline	**0.376**	**1.108**	**0.586**	**-0.438**	**0.293**	1.271	0.921
Normal Weight	**-0.360**	**-1.272**	**-0.797**	**-0.392**	**-0.032**	-0.297	-0.385
Obese	**-1.396**	**-1.776**	-0.662	-0.303	**-0.469**	-0.971	-0.683
Age <= 18	-0.602	**-0.708**	**-1.694**	**0.794**	**-1.033**	-0.393	-0.754
Age >= 65	**-0.249**	-0.550	0.387	-0.758	**0.780**	**-0.825**	**-1.040**
Female	**0.342**	0.423	0.187	0.626	**0.336**	**0.503**	**-0.641**

consistent with intuition since if the time between consumption occasions is less, consumers are more likely to switch categories and brands. The magnitude of the effect of fat and protein on utility are also different from what was estimated in the base model.

Table 3.12C. Continued MDCEV Model Utility Results

Variable	**Estimate**
Day Dependence - Category	**1.259**
Time Dependence - Category	**-0.157**
Day Dependence (Cat)* Log (Delay+1)	**-0.250**
Time Dependence (Cat)* Log (Delay+1)	**0.100**
Day Dependence - Brand	**0.185**
Time Dependence - Brand	**-0.234**
Fat	**2.259**
Carbohydrates	-0.772
Fiber	6.709
Protein	**-0.635**
At Breakfast	**0.272**
Breakfast to Lunch	**-0.144**
Lunch to Dinner	-0.476
Post Dinner	**-0.770**
Weekend	-0.053

The satiation parameters in Table 3.13A capture the diminishing marginal utility as consumption increases, conditional on the consideration set. Once the alternative enters the consideration set, the individual chooses an alternative that provides the highest utility, while the quantity consumption is governed by the observed variables. Conditioning on the predicted consideration sets, chips and puffs have the lowest satiation and highest consumption in terms of calories. Whereas the alternatives such as crackers, nuts and seeds, pastries and donuts, yogurt have high satiation parameters. Therefore, at a consumption occasion, individuals are going to consume lesser quantity or are satiated faster. We were not able to estimate satiation parameters for ice-cream, others, and pretzels. Higher carbohydrates and protein content in snacks lead to lower satiation effects – a result that is consistent with the prior model. Notice that fat and fiber are more satiating, or the individuals tend to consume less of alternatives that are high on these attributes. Finally, the time of the day effects show that higher quantity consumption happens during the earlier part of the day compared to the base (lunch and dinner snacking) and

Table 3.13A. ***MDCEV Model Satiation Parameters***

Parameter	Ice-Cream	Cakes	Candy	Chips	Cookies	Crackers	Break Fast Bars
Baseline	0.000	-1.143	-0.567	**4.182**	**-1.036**	**-1.820**	**-1.610**

Table 3.13B. ***MDCEV Model Satiation Parameters***

Parameter	Nuts	Others	Pop Corn	Pastries	Pretzels	Puffs	Yogurt
Baseline	-2.721	**0.000**	**0.277**	-2.374	0.000	**2.572**	**-2.964**

consumption at other times of the day is no different from the lunch and dinner time snacking.

Table 3.13C. ***MDCEV Model Satiation Parameters - Covariates***

Variable	**Estimate**
Normal Weight	-0.082
Obese	0.011
Age <=18	0.192
Age >=65	**0.674**
Female	**0.227**
Fat	-0.184
Carbohydrates	0.142
Fiber	**-1.635**
Protein	0.369
At Breakfast	0.521
Breakfast to Lunch	1.336
Lunch to Dinner	**0.097**
Post Dinner	-0.230
Weekend	-0.288

In the following section, we discuss two counterfactual simulations that capture the changes in terms of consumption occasion (time of the day) and substitution of product categories and how the amount of calories consumed vary across these two scenarios. The implications for policymakers, individuals, and firms are discussed in the next section.

3.6 Counterfactuals Simulations

We conduct two counterfactual simulations using the model parameters. First, we ask what happens to calories consumed if the time of consumption is changed within a day, all else remaining same. For instance, we shift the consumption of say ice-cream from the post dinner period to the afternoon. Will the calorie consumption change due to change in satiation and utility parameters? Second, we seek to evaluate the effect of substituting a snack for another at the same daypart, controlling for satiation and other effects. One may expect that this question can also be answered by seeing the difference in nutrition label information for the two snacks. But such a difference does not account for the individual characteristics, quantity consumed, and more importantly, differences in satiation.

3.6.1 Changing the time of the day

We calculate the utility derived from consuming an item at a given time of the day and by changing the time of the day, calculate the quantity that is needed to compensate in order to maintain the status quo. In Figure 3.1A, we show changes due to moving a snack from earlier in the day to late-night, or post-dinner to between lunch and dinner. We calculate the effect of this change across the sample and compare the averages and present them here. For example, a change in time for ice-cream from the afternoon to post-dinner shows an average increase of 109 calories. For cakes, the consumption increases by about 41 calories, while the change for popcorn is the lowest at 17 calories on an average. The average increase across all categories is about 71 calories for this change in time. Thus, the counterfactual simulations provide an insight into how calorie consumption would change given if consumers can be nudged to change the time of consumption within a day. The results suggest that post dinner snacking increases calories consumed in many snack categories. On the contrary, if the time of consumption is changed from post-dinner to 'between lunch and dinner', the average decrease in calorie consumption would be about 39 calories. Items that are consumed at late night (cakes, ice-cream), if they are shifted to an earlier time of the day (afternoon), calorie consumption would

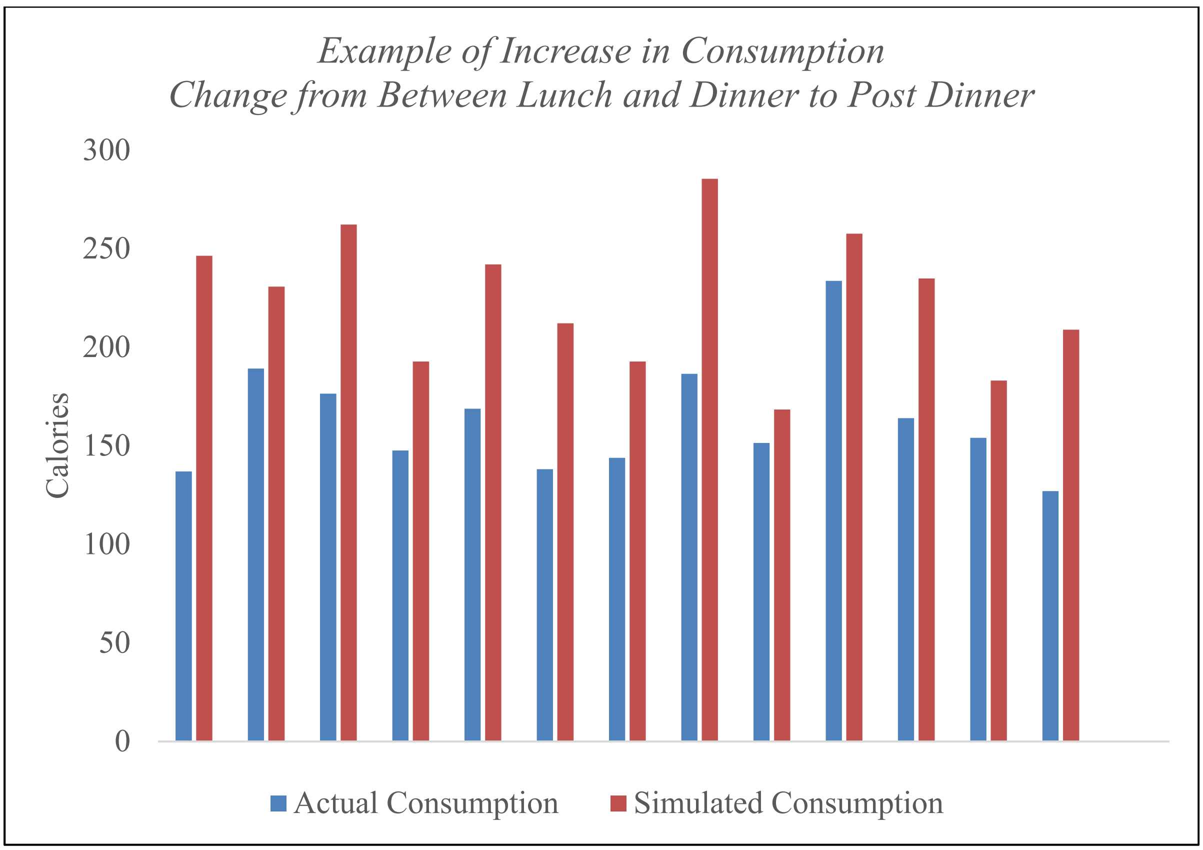

Figure 3.1A: ***Effect of Change in Time of Consumption - Increase***

decrease by a non-trivial amount. In the case of cakes, the decrease in consumption is about 31 calories, while for ice-cream it is about 49 calories. The lowest change happens for popcorn at 14 calories and the most change happens for nuts and seeds at 53 calories. Overall, these results show that by a changing the time of consumption within a day one can either increase or decrease the amount of calories consumed. In Figure 3.1B, we show changes due to moving a snack from late-night to earlier in the day.

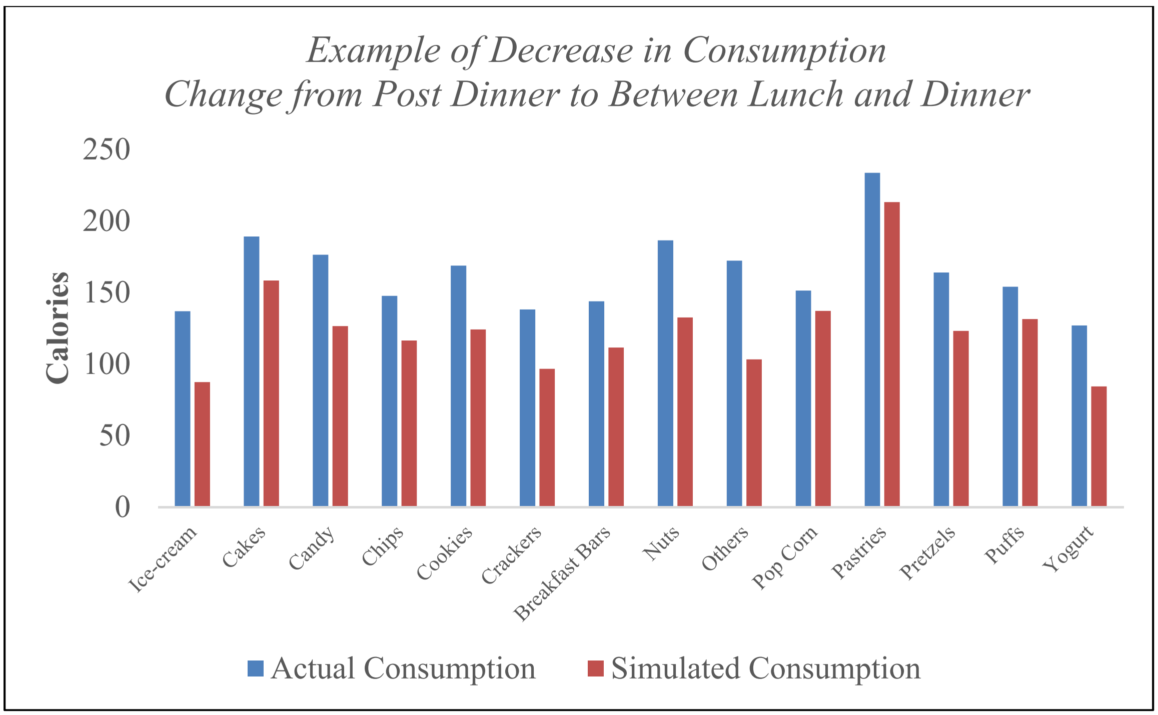

Figure 3.1B: ***Effect of Change in Time of Consumption - Decrease***

3.6.2 Category removal – Substitution with another category

We also conduct another set of counterfactual simulations, by substituting the consumed snack with another category that is a healthier alternative. In Table 3.14, we hold the time of consumption constant, we remove one category (column 1) and replace it with the category shown in column 2 based on the consumption patterns exhibited by the consumer. The estimated calories due to the switching would result in maintaining the status quo in terms of compensating utility. If chips were replaced with crackers, calorie consumption decreases by a marginal amount (3%). Similarly, switching ice-cream with yogurt could lead to an increase of about 2% in calories consumed. For pastries and donuts, the replacement with breakfast bars would result in a decrease in consumption by 24% at breakfast time and about 4% during post-dinner. And if puffs are replaced by popcorn, the increase is marginal at 0.5%. These results show the importance of category removal and switching them with an alternative and palatable category. To our knowledge, we couldn't find results that show the effect of category removal on the overall calories consumed. Similar to the counterfactuals in the previous section, if the change persists over the observation period, one can either increase or decrease overall consumption by

Table 3.14. ***Effect of Category Substitution on Calorie consumption***

Replace (Category)	With (Category)	Time of Day	Change in Calories (Average)
Chips	Crackers	Post Dinner	-3.2%
	Nuts	Post Dinner	218.6%
Candy	Nuts	Post Dinner	81.4%
Cookies	Crackers	Breakfast and Lunch	-24.2%
		Post Dinner	-18.6%
Icecream	Cakes	Post Dinner	26.8%
	Yogurt	Post Dinner	2.3%
Pastries	Breakfast Bars	Breakfast and Lunch	-23.7%
		Post Dinner	-4.4%
Puffs	Pop Corn	Post Dinner	0.5%

a non-trivial amount. For managers, these results provide insight into how a product can be positioned by the time of the day such that it benefits both the firm and the individual consumers.

Similarly, for policymakers who are working on changing dietary patterns of individuals, positioning various foods or replacing them with another category, would help combat the positive energy imbalance that is generally the cause for an increase in weight among individual consumers.

3.7 Discussion & Conclusion

When studying consumption occasions such as snacking, streaming video or music over the internet, consumers generally have access to many alternatives but restrict themselves based on their preferences to certain categories (genres). For example, a video-streaming service such as Netflix provides hundreds of movies and original shows, with a larger number of TV shows that are acquired from other studios. Given a larger catalog, consumers tend to stick to a genre or category of movies/shows. Similarly, in the context of snacking, even with a wide variety of choices, consumers generally stick to a certain type of snack depending on the time of the day. Our model captures this heterogeneity in preferences across the sample using the consideration sets model. By conditioning the model on predicted consideration sets, we overcome certain computational issues with consideration sets models. And by using a multiple discrete-continuous choice framework, we relax the limitations imposed by the traditional Logit and Probit discrete-choice models. Prior studies in marketing, with a few exceptions, (Kim et al. 2002, Dubé 2004) used the Logit or Probit framework for making predictions about consumer choices. The key limitation was the use of a linear utility function, ignoring diminishing marginal utility and restriction to a single unit of consumption (Dubé 2004). Given these limitations, the traditional models, though provide great insight into how consumers make choices, may not be able to provide insights into consumption choices such as our case (snacking). We control for demographic variables, use product and time-varying variables to study the preferences over-snacking occasions. Even with all the controls, we find a significant effect of the state variables on consumption choices, while recovering the variety-seeking behavior within a day for both category and brand choice. By studying the observed consumption patterns, we recover satiation parameters that provide an intuitive economic meaning on diminishing marginal utility. Given the nature of these structural parameters, we can run counterfactual simulations to study the effect of category removal or change in time of consumption. Our results have implications for both policymakers and managers – two parties who are interested in changing what choices consumers make in order to maintain their health. For policymakers, suggesting a small change in the time of consumption might be more practical than asking individuals to remove entire categories. For managers, repositioning products based on the time of day could help either increase or decrease calories and thus quantity consumed.

By using a multiple-discrete continuous framework, we can provide insights into the consumption patterns of individuals. We could investigate the effect of flavor, texture and other attributes at which more variety-seeking happens on consumption choices and quantity. By looking at consumption instead of purchase occasions, we overcome one of the limitations of prior studies (Dubé 2004).

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CHAPTER 4

LATENT CLASS MODEL OF SNACK CONSUMERS: AN APPLICATION OF MULTIPLE DISCRETE-CONTINUOUS CHOICE MODEL

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Abstract

In this paper, we investigate the snacking patterns of individual consumers to uncover segments that behave similarly. Snack consumption accounts for about 25% of calories and consumers make over 200 food related choices. Snack consumption is also been linked in some studies to obesity issues among US consumers. This makes it important for both policymakers and managers to understand what factors effect snack consumption. Using a rich panel data of individual level snack consumption, we first estimate a latent class model of consumer preferences using the choice data alone. We then estimate a latent class model of consumer preferences and quantity choices in a single model. Using our approach, we uncover three latent segments, and classify them as "old, overweight and inactive", "male and obese" and "young and active". These segments are based on consumer preferences and on the quantity they consumed. In traditional latent segment models that use the multinomial logit framework to uncover latent segments, we assume that consumers face constant marginal utility, thereby ignoring the aspect of quantity consumption which results in satiation or diminishing marginal utility. Our model enables us to relax this fundamental assumption and allows us to add satiation as another dimension for segmentation apart from consumer preferences. To our knowledge, this is the first paper in marketing to show that satiation can also be used an additional dimension for customer segmentation apart from consumer preferences. We contribute to the literature in two ways: using quantity consumption, we demonstrate how satiation can be used as a new dimension for segmenting customers, and we provide a better understanding and description of the differences in preferences and quantity consumption among distinct population segments.

Our model is estimated in a two-stage framework using the EM algorithm. In the first stage, we use a multinomial logit model to assign individuals to segment in a probabilistic manner. Given the segment membership, we use the multiple discrete-continuous extreme value (MDCEV) model to study the consumption choices. We estimate the latent class model with the MNL framework in a separate model. In both cases, we estimate a series of models with one to five latent segments. We find that the three-segment model provides a superior fit compared to all other models. In the MNL based framework, we describe the segments based on preferences alone. Whereas, in the MDCEV framework, we are able to describe segments based on both quantity (satiation) and preferences in a single model.

We find that category consumption is governed by habituation across days in just one of three segments. Within a day, the "male and obese" segment seeks more variety in category consumption over the other segments. We find that all three segments are brand variety-seekers within a day while habituated across days for brand choices. Preference levels for each category varies across segments. Satiation levels differ across segments – a unique feature of this model that allows us to understand quantity consumption along with preferences. Post segmentation, we create profiles for the three segments and find that the calorie consumption varies significantly across the three segments varies by categories. Consumers in these three segments differ in their satiation levels by time of day, and product characteristics. Our results have implications for managers interested in creating optimal consumption bundles and for policymakers interested in addressing over-consumption leading to obesity among US consumers.

4.1 Introduction

Marketing managers and researchers have used segmentation methods for a long time (Wedel and Kamakura 2012). Smith (1956) introduced the idea of market segmentation, which recognizes that a market consists of a number of homogenous groups of consumers who are similar within that group with respect to preferences for products but differ from others (homogeneity in heterogenous markets). Most papers in marketing rely on consumer preferences alone to segment markets (Gupta and Chintagunta 1994; Bhatnagar and Ghose 2004; Konuş, Verhoef and Neslin 2008; Popovich 2017).

The latent class models of discrete choice (Kamakura and Russell 1992) rely on two levels of multinomial logits – first to assign segment membership to each consumer and then estimate the effects of observed variables on the final choice given the segment membership. In discrete choice models, usually a single alternative is allowed to be chosen in a given occasion. These models also ignore the choice of quantity when modeling choices. In many choice occasions consumers can choose multiple alternatives (multiple discreteness) from the universal set of alternatives. Situations such as these can be seen in grocery shopping, vehicle ownership, investing in stocks (Sobhani, Eluru and Faghih-Imani 2013). Using discrete choice models in such scenarios to explain choices might not capture behavior in its entirety.

Various authors over the years have proposed solutions to handle multiple discreteness. Hendel (1999), Dubé (2004), (Kim, Allenby and Rossi, 2002) proposed methods to estimate models that explain joint consumption of multiple alternatives. Bhat (2008) proposed a closed-form solution to this problem that captures choice and quantity consumption when there is multiple discreteness. The multiple discrete-continuous extreme value (MDCEV) is easy to estimate with a large number of alternatives. There have been many extensions to the MDCEV model but the use of a latent class model in this context is rare. To the best of our knowledge there is only one other study that uses latent class segmentation on MDCEV model (Sobhani, Eluru and Faghih-Imani 2013).

Our goal in this research is to investigate the snacking patterns of individual consumers and uncover segments that behave similarly. Research indicates that consumers make more than 200 food related choices in a day (Wansink and Sobal 2007), and consumption of snacks has important implications for consumers, policymakers and managers. Consumption of snacks accounts for about 25 percent of the food intake in a day (Yogunito 2011), making them one of the main sources of energy and nutrition. Moreover, several categories such as cakes, pretzels, cookies, potato chips, popcorn and candy bars, are classified as unhealthy and often reported to be related to prevalence of obesity (Gregori, Foltran, Ghidina and Berchialla 2011). Our model allows managers to appropriately target different segments and thus create greater market share and customer satisfaction. Obesity is now recognized as a growing problem in the United States and snacking has a part to play in this. By understanding similar patterns of behavior, policy makers may also be better served in coming up with solutions to tackle this issue of obesity. Research scholars might be interested in using the model to uncover latent segments when modeling simultaneous choice and quantity decisions in various contexts that exhibit multiple discreteness (e.g., entertainment (movies and TV shows), gaming, travel, and choice of activities during leisure). For instance, people choose which show to watch and for how long and can choose to watch multiple shows in a given time slot.

Using a rich panel data of snack consumption at an individual level, we investigate presence of latent segments of snack consumers based not only on their preferences but also on the quantity consumed. In doing so, we relax the assumptions of traditional discrete choice models of single choice and constant marginal utility. That is, we are able to model consumer satiation with quantity consumed and examine whether different segments have different satiation patterns, in addition to different preferences. Consistent with existing models, we develop a two-stage model. In the first stage, we employ a multinomial logit model to assign segment membership in a probabilistic manner. In the second stage, we estimate the MDCEV model parameters conditional on latent class membership to study consumption choices. We estimate a series of models with one to five latent segments. We find that the three-segment model provides a superior fit compared to all other models.

We capture the effects of demographics and occasion specific effects on preferences and satiation across 14 snack categories in these three segments. We label these segments "inactive", "males and obese" and "active". We find that consumers are habituated to snack consumption across days in all three segments. These segments differ in their preference for different snacks at different levels. They also differ in their satiation levels – a feature of this model that allows us to understand quantity consumption (calories) along with preferences. We also find that the calorie consumption across the three segments varies by categories. Consumers in these three segments differ in their satiation levels across categories. They also differ in their satiation levels by time of day, and product characteristics. Our approach has important implications for both policymakers and marketers. To our knowledge, this is the first paper in marketing to show that quantity consumption can also be used an additional dimension for customer segmentation apart from consumer preferences. We contribute to the literature in two ways: using quantity consumption, we demonstrate how satiation can be used as a new dimension for segmenting customers, and we provide a better understanding and description of the differences in preferences and quantity consumption among distinct population segments.

We organize the paper as follows. We first provide an overview of literature in multiple discrete-continuous choice models and latent segmentation models. We then describe the empirical model and the estimation procedure. We provide an overview of the data that was used for this paper. We then discuss the model results and their implications. Finally, we conclude with a discussion of limitations of our model and present ideas for future research.

4.2 Literature Review

Various approaches have been proposed over the years to identify customer segments in marketing. Frank, Massey and Wind (1972), Wind (1978) discuss different variables and methods on how to identify customer segments. Observed characteristics such as demographics, purchase amount, products purchased, frequency were often used to classify customers into various segments. From the works of Green, Carmone and Wachspress (1976), Dunn, Reader and Wrigley (1987), Desarbo and Cron (1988), Kamakura and Russell (1989) we were provided with a framework for identifying latent segments – customers assumed to be part of unobserved segments based on observed characteristics and choices. The seminal work of Kamakura and Russell (1989) provided a simple and elegant way to identify segments using consumer demand data. They use ketchup purchase data to demonstrate how a market can be segmented based on consumer preferences. By combining the works of Kamakura and Russell (1989) and Dayton and Macready (1988), Gupta and Chintagunta (1994) show that the segmentation probabilities in a logistic mixture model can be calculated by adding customer demographics as explanatory variables. This approach gives an actionable information because segments are now based on observable characteristics of individuals. Other researchers have used the latent segment models for segmentation of customers based on purchase histories. Bucklin and Gupta (1992), use a nested multinomial logit model with latent segments in the case of liquid laundry detergent consumers. Grover and Srinivasan (1987) use the latent class model to define segments and define the competitive market structure using panel data of instant coffee purchases. Further, in consumer behavior side, papers by Kamakura and Mazzon (1991), Kamakura and Novak (1992) use the latent segment model to identify segments of population that display distinct value systems. Lehmann, Moore and Elrod (1982) identify two segments of individuals who differ in the extent to which they acquire information. They classify consumers into two groups – one that collects no additional information prior to purchase and another that exhibits medium amount of search. They also suggest that consumers switch between these two segments.

In most the prior research, latent segments were studied using the multinomial logit (MNL) model in both the segment formation phase as well as the choice phase. In these discrete choice model, researchers examined the drivers of a single choice decision of a brand (within a product category) made by individuals from a set of alternatives that were considered perfect substitutes (Kamakura and Russell, 1989). The MNL framework also assumes that consumers face constant marginal utility. Further, in many consumption or shopping scenarios, consumers are faced with imperfect substitutes (grocery purchase, movie and music selection) and tend to make more than one choice at a given occasion. In order to incorporate multiple choices (multiple discreteness) and diminishing marginal utility due to quantity consumption (a continuous variable), researchers have proposed methods that can capture consumption behavior in a better way. One of the first solutions to address multiple discreteness in the context of choice of personal computers was provided by Hendel (1999). In grocery shopping, there are product categories where one chooses a variety of flavors of ice-cream or yogurt (Kim, Allenby and Rossi 2002), buy multiple varieties of soft drinks (Dubé 2004) in a given trip or occasion. This phenomenon called multiple discreteness, cannot be modeled using a discrete choice model and so the authors developed different solutions based on random utility maximization (RUM). However, the models rely on the assumption of a Normal distribution and are not easy to compute with a large number of alternatives. Bhat (2005) also use RUM to develop an easy to estimate model using the assumption of extreme value distribution and called it MDCEV (multiple discrete-continuous extreme value) model. They show that the model reduces to a multinomial logit model for a single choice. Further, researchers have used the MDCEV model to model individual's own and use multiple automobiles (Bhat 2008), make time allocation decisions across multiple leisure activities (Luo, Ratchford and Yang 2013).

In the latent class framework, most papers in marketing use preference data to find latent segments. To our knowledge only one paper in transportation science studies latent segment models using the MDCEV framework (Sobhani, Eluru and Faghih-Imani 2013). The earliest papers in marketing such as Kamakura and Russell (1989) do not consider quantity purchases as a factor for segmentation. Based on the framework of Bhat (2008), we now know that it is essential to include quantity consumption along with preference data to capture individual behavior fully. We see that individuals exhibit diminishing marginal utility and can choose multiple items at the same time – which is a drawback for models using the latent class MNL framework. Thus, our paper tries to fill this gap by implementing a latent class MDCEV framework using a rich panel dataset that captures snacking behavior of individuals.

4.3 Empirical Model and Estimation

In order to identify latent segments of snack consumers, we begin with an assumption that the consumers in our dataset belong to "S" segments. The segment membership of each individual is unobserved by the researcher. The number of segments is also an unknown factor that needs to be estimated. Each individual, within a segment, makes multiple choices at a given occasion. In our case, a consumer could choose pastries and breakfast bars or nuts during breakfast, chips and crackers during lunch. We consider the utility function proposed by Bhat (2008), which allows zero consumption of all goods. This assumption is plausible because individuals in our dataset don't consume snacks at all consumption occasions. They could skip snacking at a given daypart, and this utility function allows us to capture such behavior. We assume that the individuals (*i = 1,2,…,I*) are utility maximizers, can choose from *k* alternatives (*k = 1,2,…,K*) at a given day part *t* (*t = 1,2,….,T*) and derive utility from consuming more than one alternative in that day part.

$$U_{ids}(\boldsymbol{c}) = \sum_{k=1}^{K} \frac{\gamma_{ks}}{\alpha_{ks}} \Psi_{ikds} \left\{ \left(\frac{c_k}{\gamma_{ks}} + 1 \right)^{\alpha_{ks}} - 1 \right\} \tag{1}$$

c_{ikt} is the quantity (calories) consumed by individual *i* from category *k* at daypart *t.* α_{ks} is defined as the satiation parameter, which is constrained to be in between 0 and 1. $\boldsymbol{c}$ is the vector of consumption quantities. This allows us to capture the diminishing marginal utility from consumption of a given snack. As $\alpha_{ks} \rightarrow 0$, satiation increases, and individuals tend to consume lower quantities of the item and as $\alpha_{ks} \rightarrow 1$, satiation decreases and consumption increases.

$\gamma_{ks}(> 0 \, \forall \, k)$ is defined as the translation parameter, that allows for zero consumption of the goods. $\alpha_{ks}$and γ_{ks} cannot be jointly estimated due to identification issues. We set one of them to a constant and the other is estimated. We estimate a model that allows α_{ks} to vary across product categories and is defined as a function of individual, product characteristics and the time of the day. This allows us to capture differences between individuals and find how satiation varies by time of the day. We parametrize α_{ks} as follows,

$$\alpha_{ks} = \frac{1}{1+\exp(-Y\beta_{ks})} \tag{2}$$

Y is a matrix of individual and product characteristics, occasion specific covariates (daypart, weekend or weekday).

Ψ_{ks} captures the utility of choosing an alternative (at zero consumption). We allow Ψ_{ks} to be a function of individual demographics, product characteristics and time of consumption. We re-write the utility function that is used for estimation in our model as follows:

$$U_{ids}(\boldsymbol{c}) = \sum_{k=1}^{K} \frac{1}{\alpha_{ks}} \Psi_{ks}\{(c_k + 1)^{\alpha_{ks}} - 1\} \tag{4}$$

The baseline utility function is written with the stochastic component as

$$\Psi_{ks} = \Psi'_{ks}(Z)e^{\epsilon_{ks}} \tag{5}$$

where, Z is a matrix of individual demographics, product characteristics and occasion specific variables. We further parametrized $\Psi'_{ks}(Z)$ as a $exp(Z\beta_k)$, thus enabling us to write the baseline utility of consumping alternative k as

$$\Psi_{ks} = \exp(Z\beta_{ks} + \epsilon_{ks}) \tag{6}$$

The individual is maximizing his utility from consumer some or all of the *k* items subject to the budget constraint $\sum_{k=1}^{K} c_{ikt} = C_{it}$, where C_{it} is the total calories that an individual wishes to consume at an occasion. Thus, the utility function can be further written as,

$$U_{ids}(\boldsymbol{c}) = \sum_{k=1}^{K} \frac{1}{\alpha_{ks}} \exp(Z\beta_{ks} + \epsilon_{ks}) \{(c_k + 1)^{\alpha_{ks}} - 1\} \tag{7}$$

Using the budget constraint and equation (7), we solve for the optimal consumption allocations by writing the appropriate Lagrangian and applying the KKT (Karush Kuhn-Tucker) conditions.

$$\mathcal{L} = \sum_{k=1}^{K} \frac{1}{\alpha_{ks}} \exp(Z\beta_{ks} + \epsilon_{ks}) \{(c_k + 1)^{\alpha_{ks}} - 1\} - \lambda(\sum_{k=1}^{K} c_k = C_{it}) \tag{8}$$

Following Bhat (2008), we solve for the optimal consumption decisions (c_{ikt}^*) to arrive at the KKT first order conditions as:

$$V_{ikds} + \epsilon_{ks} = V_{i1ds} + \epsilon_{1s} \text{ if } c_k^* > 0 \ \forall k = 2,3, \dots, K \tag{9}$$

$$V_{ikds} + \epsilon_{ks} < V_{i1ds} + \epsilon_{1s} \text{ if } c_k^* = 0 \ \forall k = 2,3, \dots, K \tag{10}$$

$$V_{ikds} = Z\beta_{ks} + (\alpha_{ks} - 1)\ln(c_k^* + 1) \tag{11}$$

Like in all discrete choice models, parameters for one of the categories cannot be identified. We designate ice-cream as the base good, for which the utility is set to zero ($\beta_{icecream,s} = 0$). Z contains an intercept term for the rest of the categories that captures category specific preferences. Similarly, parameters for demographics (invariant across categories) are estimated for each category, while product specific and occasion specific parameters are fixed across categories. Assuming that ϵ_{ks} is i.i.d extreme value, we derive the following closed-form solution for the probability that the individual consumes *J* of the *K* goods:

$$P(c_1, c_2, \dots c_k, 0,0, \dots,0 | i \in s) = \prod_{k=1}^{J} \left(\frac{1-\alpha_{ks}}{c_{itk}+1}\right) \sum_{k}^{J} \left(\frac{c_{itk}+1}{1-\alpha_{ks}}\right) \prod_{k}^{J} \frac{exp^{Z\beta_{ks}+(\alpha_{ks}-1)\ln(c_{itk}^*+1)}}{\sum \exp^{Z\beta_{js}+(\alpha_{js}-1)\ln(c_{itj}^*+1)}} (J-1)!$$

(12)

We designate this probability as $P(MDCEV|s)$, the probability of choosing a group of alternatives at a choice occasion, conditional on the segment membership of the individual. The second part of the latent class segmentation model involves identifying the segment to which a customer belongs. This segment membership is unobserved by the researcher. We let the probability that an individual belongs to a segment be a function of individual characteristics.

$$q_{is} = X\beta_s + \epsilon_{is} \tag{13}$$

X is a matrix of individual characteristics, β_s is a vector of parameters that need to be estimated, ϵ_{is} is the stochastic component of the utility term. Individual could belong to one of the S segments, and by assuming that the stochastic component is i.i.d extreme value, we get to the familiar multinomial logistic model:

$$P(q_{is}) = \frac{\exp^{X\beta_s}}{\sum_{r=1}^{S} \exp^{X\beta_r}} \tag{14}$$

Combining equation (12) and (14), we derive the unconditional probability of an individual choosing K alternatives as:

$$P(MDCEV) = \sum P(q_{is}) P(MDCEV|i \in s) \tag{15}$$

Further, this can be written as, $P(MDCEV) =$

$$\sum P(q_{is}) \prod_{k=1}^{J} \left(\frac{1-\alpha_{ks}}{c_k+1}\right) \prod_{k}^{J} \left(\frac{c_k+1}{1-\alpha_{ks}}\right) \prod_{k}^{J} \frac{exp^{Z\beta_{ks}+(\alpha_{ks}-1)\ln(c_k^*+1)}}{\sum \exp^{Z\beta_{js}+(\alpha_{js}-1)\ln(c_j^*+1)}} (J-1)! \tag{16}$$

We call the formulation in equation (16) as the latent class MDCEV (LC-MDCEV) model. The parameters to be estimated are β_s, α_{ks} and β_{ks}. The likelihood function based on equation (16) is further written as,

$$L(\beta_s, \alpha_{ks}, \beta_{ks}; X, Z) = \prod_i^N \sum P(q_{is}) \prod_{k=1}^J \left(\frac{1-\alpha_{ks}}{c_k+1}\right) \prod_k^J \left(\frac{c_k+1}{1-\alpha_{ks}}\right) \prod_k^J \frac{exp^{Z\beta_{ks}+(\alpha_{ks}-1)\ln(c_k^*+1)}}{\sum \exp^{Z\beta_{js}+(\alpha_{js}-1)\ln(c_j^*+1)}} (J-1)!$$

(17)

A discrete choice model with a closed-form solution can be easily estimated using standard gradient descent algorithms. However, in a latent segment model, the segment membership is unknown, rendering it difficult to estimate and can become computationally unstable if we attempt a maximum likelihood procedure (Bhat, 1997). To address this issue, we estimate the model using the EM (Expectation-Maximization) algorithm. EM algorithm was successfully used to estimate models with missing data (Dempster, Laird and Rubin, 1977). Treating segment membership as the missing information, we re-write the log-likelihood function as follows:

$$LL = \sum \log(\sum_i^N P(q_{is}) P(MDCEV|s)) \quad (18)$$

If we knew the segment membership, the log-likelihood function would be written as,

$$LL = \sum \log\left(\sum_i^N \left(P(q_{is})\right)^{\delta_{is}} P(MDCEV|s)\right) \quad (19)$$

where $\delta_{is} = 1$, if $i \in s$, otherwise $\delta_{is} = 0$. Following Bhat (1997), the expected segment membership of individual *i* can be written as a function of the prior segment membership $P(q_{is})$ as,

$$\hat{P}(q_{is}) = \frac{P(q_{is}) P(MDCEV|s)}{\sum_{r=1}^S P(q_{ir}) P(MDCEV|r)} \quad (20)$$

Further, $LL = \sum_i \sum_s \hat{P}(q_{is})\left(\log\left(P(MDCEV|s)\right) + \log\left(\mathrm{P}(\mathrm{q_{is}})\right)\right)$ (21)

Using equations (20) and (21), we go through two steps (E and M) for estimating the unknown parameters as follows:

1) We assume that there are *S* segments into which individuals can be divided.

2) We begin with a set of starting values ($\theta_0 = (\alpha_{ks0}, \beta_{ks0}, \beta_{s0})$)

3) In the E step, using equation (20), we calculate the expected membership of the individual, given the starting values.

4) We then maximize equation (21) in the M step to arrive at a new set of parameters θ_1

5) We loop through steps (3) and (4) till the log-likelihood value doesn't change anymore. Once we reach a stable set of parameter values, we stop the EM algorithm. Using these parameters, we can estimate the standard errors (EM algorithm doesn't generate standard errors), using a standard maximum likelihood estimation software. We start with $S=1$, assuming that there is only 1 segment. We then re-estimate the model with $S = 2,3,\ldots,5$. In order to choose the model that provides the best fit, we calculate the Bayesian Information Criterion (BIC) values, which takes into consideration the sample size and penalizes models for complexity (more parameters).

We also estimate a latent class multinomial logit model (LC-MNL) that is derived based on the work of Gupta and Chintagunta (1994). We use demographics to assign segment membership and conditional on that, we estimate the parameters of the choice model in the second stage. Notice that in the MNL model, an individual can choose only one item at a time. Therefore, the data structure that is used for this model changes. Instead of a consumer choosing multiple items in a given occasion, we model each choice that consumer makes separately. Therefore, the number of observations in the dataset increase according to the number of total choices made. For example, in an occasion a consumer may have chosen crackers and chips in that order. When we estimate the MNL model, we estimate the choice of crackers as one data point and the choice of chips as another data point. In the MDCEV model, we can treat these joint choices as occurring during one occasion or one single data point.

The probability that a consumer chooses one category k is given as:

$$P(k|i \in s) = \frac{exp^{Z\theta_{ks}}}{1+\sum_{j=2}^{K} \exp^{Z\theta_{js}}} \tag{22}$$

Combining equations (14) and (22), the probability that an individual *i* chooses category *k* is written as:

$$P(k) = \sum_{s=1}^{S} \frac{\exp^{X\beta_s}}{1+\sum_{r=2}^{S} \exp^{X\beta_r}} \frac{exp^{Z\theta_{ks}}}{1+\sum \exp^{Z\theta_{js}}} \tag{23}$$

The log-likelihood function that will be used for estimation is written as,

$$LL_{MNL} = \sum_i \log\{\sum_{s=1}^{S} \frac{\exp^{X\beta_s}}{1+\sum_{r=2}^{S} \exp^{X\beta_r}} \frac{exp^{Z\theta_{ks}}}{1+\sum \exp^{Z\theta_{js}}}\} \tag{24}$$

Following Bhat (1997), we estimate this model in a similar fashion as explained in the EM algorithm procedure above. We run the model to estimate parameters and stop when there is little to no change in the log-likelihood value over consecutive iterations. We then use the estimated parameters to find the standard errors using a standard optimization procedure.

Both models (LC-MDCEV and LC-MNL), consist of a first stage (LC) model where we estimate segment membership as a function of demographic variables. Gupta and Chintagunta (1994) use demographic variables as characterizing the segment membership of individuals in their sample. Our approach is similar to theirs for the LC-MNL model. Thus, the matrix *X* in the first stage estimation for equation (14) consists of *S-1* intercepts and demographic variables. We use age, gender, BMI group, level of physical activity to classify individuals into different segments. For identification purpose, as in any discrete choice model, we set the parameters of the first segment to zero and estimate segment membership parameters for the each of the *S-1* segments.

In the second stage, we estimate the parameters that describe the choices made by the consumers. The matrix Z in both equations (12) and (22) consist of intercept terms, state-dependence terms, product characteristics and occasion specific variables (time of the day, weekend or weekday). We use four state-dependence terms to capture variety seeking or inertial behavior. Following Khare and Inman (2009), we call these time dependence (across different time periods within a day) and day dependence (across days but at the same time period) – both for category and brand. In order to capture decay of state-dependence over time (Trivedi et al. 1994; Seetharaman et al. 1999) we use category specific *wearout* terms. Following Seetharaman et al. (1999), we interact the state dependence terms with the logarithm of gap (*log(t+1)*) between consumption occasions. We expect that as the gap (t) between consumption occasion increases, we should find inertial behavior among the consumers. Consistent with Seetharaman et al. (1999), we use a logarithmic form of t (log(t+1)) to capture delay. 't+1' is to ensure that logarithmic function is meaningful when t=0 (consider choice of two items at the same time). We use *'t'* for time and *'d'* for day dependence. We also control for the product characteristics such as Fat, Protein, Carbohydrates and Fiber content. We include time of the day (dayparts) in the model along with day specific effects to capture any differences in consumption patterns due to weekends or weekdays. We capture individual specific effects through age groups, gender and weight groups. Overall, we estimate 8 parameters per segment in the first stage (LC) and 28 parameters in the MNL model in the second stage for the LC-MNL model. Whereas, in the second stage of the LC-MDCEV model, we estimate 51 parameters for the utility (28) and satiation (23) specification per segment. In the next section, we provide details about the data that was used for this analysis.

4.4 Data

We use the data provided by a large US based snack manufacturer. The firm recruits a random sample of participants who provide snacking records over a period of two weeks. They use a mobile device to record their snacking activity across multiple occasions over these 14 days. Information collection includes demographics, day and time of snacking, amount of snacks consumed, brand and category level information. The data is collected in real-time and validated by the firm at the end of the sampling period. The data collection exercise captures rich information about the participants, especially, age, gender, race, region, household size, height, weight, income, race, marital status, education, and location. We also capture data about the amount of physical activity that a consumer is involved in, in the sampling period. We have three levels of physical activity – low, medium and high exercise conditions.

The sample that was provided to us has about 1,811 participants. They recorded about 21,145 snacking occasions. Each snacking occasion involves consumption of at least one snack. Our data captures information on about 800 brands that were classified into 14 different categories. Note that we focus on snacks that are sold in stores and come in standard packs. We do not focus on non-standard items such as fruits or vegetable-based snacks as the information that we need for our model is not readily available for such categories. In order to capture interesting aspects about the snacking behavior, we focus on consumers who reported consistently for at least 10 of the 14 days. After resampling, we chose about 341 consumers who reported 5327 snacking occasions. Note that in the MDCEV model a snacking occasion would mean a day-part – where consumers can choose multiple snacks. In the MNL model, this breaks down to the particular snacking occasion, where each snack is treated as a snacking occasion. Thus, for the MNL model we have 6,152 snacking occasions. About 13% of the time, consumers have chosen more than 1 item (multiple discreteness) in a consumption occasion. We use ice-cream as the base category, while the thirteen categories are - chips, candy, cookies, crackers, pastries, cakes, energy bars, nuts, popcorn, pretzels, puffs, yogurt and others. The category "others" includes meat-based snacks (e.g. beef jerky). The snack taxonomy is based on standard industry practice. Based on quantity consumed at each occasion and the nutrition label information, we calculated the total calorie intake for an individual for each occasion as:

$$c_{it} = \sum_{k=1}^{K} Cal_k * Q_{ik} \tag{25}$$

i = 1, ..., I (indexes the individual),

k = 1, …, K (category consumed)

Cal_k = calorie per serving from category *k*

Q_{ik} = quantity consumed (in servings) by individual *i* in category *k*

c_{it} = Total calories consumed at an occasion *t* by individual *i*

Table 2.2A shows the key demographic variables that affect snacking. We have 54.8% males in the sample. We use BMI to classify individuals into three groups – normal weight (37%), over-weight (30%), and obese (33%). We also have the age groups classified as "18 and under", 19-64 and those above "65 and over". On an average, the age group 19-64 consumed more snack calories in our dataset. Table 2.2B shows the percentage frequency and average calories consumed across the 14 categories. Chips, chocolate/candy and cookies are the most snacked items.

We divide each day into six dayparts. Breakfast (BF), between breakfast and lunch (BL), lunch (L), between lunch and dinner (LD), dinner (D) and after dinner (AD). Table 2.3 shows the average amount of calories consumed across the six dayparts. Most snacking occurs between meals – about 73%, whereas mealtime snacking accounts for only 27% of the time. In Table 2.4, we show the percentage of consumption occasions by daypart. At BF, as expected most of the snacking is from pastries and breakfast bars. Chips are the most snacked items at Lunch and at Dinner. Late night (AD) snacking mostly consists of candy, cookies and ice-cream. The five most frequently consumed categories are highlighted in bold.

4.5 Results

4.5.1 LC-MNL Model

We first present the results for the LC-MNL model. We begin with a discussion on the model fit statistics for choosing the appropriate number of segments. We then discuss the characteristics of the segments based on MNL model for the chosen number of segments. Note that the MNL model is designed to capture behavior through choices alone and ignores the quantity consumption aspect. In Table 4.1, we show the results for the LC-MNL model fit. We estimate four models – a single segment standard MNL model, a 2-, 3- and 4-segment MNL model. Our goal here is not to discuss the characteristics of the LC-MNL segments but to contrast and discuss these results with those generated from the LC-MDCEV model.

Table 4.1. ***Model Fitness LC-MNL***

Models	Observations	Parameters	LL	AIC	BIC
MNL Model	6152	28	-14581.26	29218.52	29406.80
2 Segment	6152	64	-14339.73	28807.46	29237.83
3 Segment	6152	100	-14095.81	**28391.63**	**29064.08**
4 Segment	6152	136	**-14092.88**	28457.76	29372.29

Looking at the BIC values in Table 4.1, the 3-segment LC-MNL model is sufficient to define segments of snack consumers based on our dataset. We see a steady increase in the log-likelihood value from the standard MNL model to the 4-segment solution. However, the BIC value, which penalizes complexity in models, shows that the 3-segment model is superior to the rest of the solutions. Table 4.2A provides the parameter estimates that capture the role played by the demographic variables in generating the latent segment membership of the individuals in the dataset. The parameters for the first segment are set to zero for identification in the panels of Table 4.2.

We see that segment 2 is more likely to have individuals with normal weight, under 18, and those who are more likely to indulge in low exercise. Segment 3 is more likely to have females and those under 18. To get a clearer picture of the segment membership, we calculate the

Table 4.2A. ***LC-MNL Segment Membership Results***

	Segment 1	Segment 2	Segment 3
Segmentation Variables	Estimates		
Intercept	0.000	-0.242	0.183
Normal Weight	0.000	**0.620***	0.006
Obese	0.000	**-0.116**	-0.169
Age Under 18	0.000	**0.322**	**0.764**
Age Over 65	0.000	**-1.336**	0.048
Female	0.000	0.202	**0.358**
Low Exercise	0.000	**0.738**	-0.038
Medium Exercise	0.000	***0.083****	-0.272

* bold indicates p-value < 0.05
** italics indicates parameter is significant at 10%

probability of each individual being in each segment using the MNL formulation. We predict the membership based on the highest probability rule (Gupta and Chintagunta 1994).

Table 4.2B. ***LC-MNL Segment Description by Demographics***

	Segment 1	Segment 2	Segment 3
Segment size	28.6%	32.8%	39.6%
Normal Weight	5.6%	72.2%	22.2%
Overweight	20.4%	37.9%	41.7%
Obese	33.0%	21.4%	45.5%
Age <=18	0.0%	21.6%	78.4%
Age 19-64	20.3%	61.6%	18.1%
Age >=65	25.4%	0.0%	74.6%
Female	0.0%	50.0%	50.0%
Male	34.8%	41.2%	24.1%
Low Exercise	0.0%	76.7%	23.3%
Medium Exercise	36.9%	28.4%	34.7%
High Exercise	0.0%	30.6%	69.4%

We present those results in Table 4.2B. After assigning the individuals to each segment, we calculate the segment characteristics. The first row of this table shows the segment size. Segment-3 is the largest with about 39.6% of the 341 individuals, followed by segment-2 and segment-1. We label each segment as follows: Segment-1 as "males and occasionally active", Segment-2 as "normal and inactive" and Segment -3 as "young, obese and active". We also show the demographic characteristics of the three segments in Table 4.2B. Most normal weight individuals fall in segment-2, while most obese and overweight individuals fall in segment-3. The age-groups under 18 and over 65 mostly fall in Segment-3, while most of the 19-64 fall in segment-2. Females are either in segment-2 or -3, while segment-1 consists entirely of males.

The preference parameters are provided in Table 4.2C. We see that segment 2 prefers most snacks compared to ice-cream, which is the base category. Segment 1 consists of individuals who seem to prefer nuts over ice-cream, and less likely to choose cakes, pretzels, puffs and yogurt over ice-cream. Segment 3 preference parameters suggest that most individuals in this group are less likely to choose most snacks over ice-cream. Candy, yogurt, pastries are the only categories that are equal in preference to ice-cream. These results are interesting as they provide

Table 4.2C. ***LC-MNL Second Stage Results***

MNL	Segment 1	Segment 2	Segment 3
Variable	Utility Parameters		
Ice-cream	0.00	0.00	0.00
Cakes	**-1.04**	**3.02**	**-0.77**
Candy	0.37	**4.22**	-0.08
Chips	0.50	**4.19**	**-0.12**
Cookies	0.35	**3.90**	**-0.25**
Crackers	-0.60	**3.52**	**-0.22**
BF Bars	-0.55	**3.12**	**-0.37**
Nuts	**0.79**	**3.50**	**-0.34**
Others	0.20	**3.35**	**-0.26**
Pop Corn	-0.20	**3.15**	**-0.58**
Pastries	-0.60	**3.58**	-0.12
Pretzels	**-1.12**	**3.51**	**-0.82**
Puffs	**-1.13**	**3.00**	**-1.90**
Yogurt	**-2.21**	**1.66**	-0.16
Day Dependence – Category	**1.09**	**1.53**	**2.61**
Time Dependence – Category	0.20	0.12	**0.34**
Day Dependence (Cat)* Log (Delay+1)	0.05	-0.12	**0.17**
Time Dependence (Cat)* Log (Delay+1)	0.20	0.04	0.20
Day Dependence - Brand	**1.58**	**0.88**	**1.18**
Time Dependence - Brand	**-1.08**	-0.25	**-1.74**
Fat	**3.82**	**-3.34**	**0.49**
Carbohydrates	**-2.86**	**5.98**	**-1.41**
Fiber	**1.63**	0.45	**2.25**
Protein	**-2.24**	-0.40	**-0.43**
BF	0.42	3.08	-0.07
BL	0.04	0.65	**0.51**
LD	**-0.23**	4.32	**1.23**
PD	-0.12	6.07	**0.57**
Weekend	-0.16	2.84	**-0.26**

segment level preferences which seem to show how individual segments differ in their preferences for snacking. The state-dependence parameters are mostly consistent across segments. Segments 1 and 2 are to a degree less habituated within a day – as seen by the significance of the time dependence variables. This is in contrast to the strong habituation display based on the day dependence variables. The brand time dependence variable suggests that individuals in segment two are less variety-seekers compared the other two segments. The segments also differ in their preference for the nutrients – segment 1 and 2 seem to prefer snacks higher on fat, fiber and seem to have a lower preference for snacks that are high in protein. Segment 2 seems to prefer snacks high on carbohydrates, and those low on fat. Time of the day and weekend effects were not pronounced in the segment 2. There is no significant difference in these variables compared to the base category – at lunch and at dinner snacking for time of day and weekday snacking. This suggests that individuals in segment 2 seem to snack at all the times of the day and exhibit no difference between weekend and weekday snacking. Segment 3 prefers to snack at later in the day while segment 1 seems to snack lesser during LD (between lunch and dinner). These estimates give us a good idea about snacking preferences of individuals across three segments, while ignoring the quantity choice aspect, which is an important aspect of snacking. In order to address this issue, we present the results for the LC-MDCEV model in the following paragraphs.

4.5.2 LC-MDCEV Model

Table 4.3 provides the model fit statistics for the LC-MDCEV model. Here again, a three-segment model seems to provide the best fit based on the values in the BIC column. Notice that

Table 4.3. ***Model Fitness LC-MDCEV***

Models	Observations	Parameters	*LL*	AIC	BIC
1 Segment MDCEV Model (with Demographics in Utility & Satiation)	5327	121	-14275.1	28792.2	29588.4
1 Segment Mixed MDCEV Model (with Demographics in Utility & Satiation)	5327	144	-14198.5	28685.0	29632.6
2 Segment MDCEV	5327	110	-14016.0	28252.0	28975.9
3 Segment MDCEV	5327	169	-13737.4	27812.7	**28924.8**
4 Segment MDCEV	5327	228	-13656.2	27768.3	29268.7
5 Segment MDCEV	5327	287	**-13536.6**	**27647.1**	29535.8

the number of parameters here are much larger than the MNL model as we estimate an additional set of parameters that capture the satiation effects due to quantity consumption. The first two rows show the outcomes for a single-segment MDCEV model without and with random intercepts in utility and satiation specification. In order to find the segment size that best fits our data, we estimate four different models beginning with $S=2$ to $S=5$. The log-likelihood values increase progressively, however after the three-segment model, the value of BIC starts to increase. Using the BIC value, we suggest that the 3-segment model best fits our model. The loglikelihood value for this model is superior to the model with random effects in the second row.

In Table 4.4A, we provide the results for the first stage of the LC-MDCEV model. As discussed earlier, we estimate the segment membership probability for each individual and assign them to one of the three segments. Table 4.4B shows the characteristics of each segment

Table 4.4A. ***LC-MDCEV Segment Membership Results***

	Segment 1	Segment 2	Segment 3
Segmentation Variables	Estimates		
Intercept	0.000	**-0.217**	**0.907**
Normal Weight	0.000	**-0.373**	**0.142**
Obese	0.000	**1.480**	**-0.323**
Age Under 18	0.000	**0.214**	**-0.053**
Age Over 65	0.000	**-0.262**	**-0.848**
Female	0.000	**0.448**	**-0.404**
Low Exercise	0.000	**-0.336**	**-1.069**
Medium Exercise	0.000	**-0.486**	**0.167**

based on the assigned segments. The first row represents the segment size, of the 341 individuals, 45.2% fall in segment 2, 35.8% in segment 3 and the rest in segment 1. Second row onwards represents a demographic variable (Example 'Female') and the percentage of individuals in each segment from that variable. For example, of the 154 females, 34.4% are in segment 1, 24.7% in segment 2 and the rest in segment 3. Normal weight individuals are distributed among segments 1 and 2, most of them falling in segment 3. Overweight individuals are more likely to be in segment 1. Segment 2 consists entirely of obese individuals. Those under 18 are mostly in segment 3, while those in 19-64 group are also likely to be in segment 3.

Table 4.4B. ***LC-MDCEV Segment Description by Demographics***

	Segment 1	Segment 2	Segment 3
Segment size	19.1%	45.2%	35.8%
Normal Weight	31.7%	0.0%	68.3%
Overweight	52.4%	0.0%	47.6%
Obese	0.0%	100.0%	0.0%
Age <=18	10.8%	27.0%	62.2%
Age 19-64	26.2%	32.5%	41.4%
Age >=65	41.8%	37.3%	20.9%
Female	34.4%	24.7%	40.9%
Male	21.9%	39.6%	38.5%
Low Exercise	68.1%	31.9%	0.0%
Medium Exercise	7.4%	34.7%	58.0%
High Exercise	4.1%	28.6%	67.3%

Segment 1 captures most of those over 65. Most females fall in segment 3, while most males are in segment 2 with almost an equal proportion in segment 3. Individuals who indicated that they are likely to indulge in low physical activity are mostly in segment 1,

whereas most medium and high exercise are in segment 3. Segment 2 has the second most of all exercise related categories. We label each segment as follows: Segment-1 as "old, overweight and inactive", Segment-2 as "male and obese" and Segment -3 as "young and active".

4.5.3 Utility and Satiation Profile for Segment 1

The first column of Table 4.15A provides the utility and satiation parameters for the 'old, overweight and inactive' segment. The baseline utility for candy, chips, cookies, crackers and nuts seems higher than that of ice-cream and that for pretzels and puffs is lower than that of ice-

Table 4.5A. ***LC-MDCEV Second Stage Results***

	Segment 1		Segment 2		Segment 3	
Parameter	Utility	Satiation	Utility	Satiation	Utility	Satiation
Ice-cream	0.00	**-3.02***	0.00	**0.332**	0.00	0.52
Cakes	-0.55	0.67	**0.22**	**0.100**	0.05	1.45
Candy	**0.49**	0.10	**0.10**	**-0.281**	1.19	0.00
Chips	**0.51**	0.71	**0.12**	**0.117**	1.13	**-0.80**
Cookies	**0.51**	0.82	**0.12**	0.093	0.93	**0.51**
Crackers	**0.13**	**-1.86**	**0.83**	0.063	0.56	**0.21**
Breakfast Bars	0.49	1.52	**-0.42**	0.043	**0.24**	**0.18**
Nuts	**0.82**	-0.30	**1.25**	**-0.574**	**0.60**	**0.03**
Others	0.45	**-3.12**	**-1.49**	0.043	0.64	**0.13**
Popcorn	0.24	-0.01	**-0.45**	0.028	0.23	**1.86**
Pastries	0.24	0.98	**0.29**	**0.160**	0.65	**-1.46**
Pretzels	**-0.89**	0.83	**-0.50**	0.029	0.48	**-0.51**
Puffs	**-1.49**	-0.65	**-0.58**	0.020	-0.14	**-2.16**
Yogurt	0.33	**-1.42**	**-0.03**	**0.164**	**0.19**	**0.08**

* bold indicates p-value < 0.05

cream. This makes intuitive sense because it shows that those who are 'old, overweight and inactive' seem to prefer categories that are considered less healthy. The second column shows the satiation parameters for the same segment. We interpret the result as follows: a positive sign indicates higher consumption or lower satiation. Therefore, the results indicate that individuals satiate higher (or consume lower calories) of ice-cream, crackers, 'other' snacks and yogurt. This gives a new intuition to consumption characteristics of those who are 'old, overweight and inactive'. The LC-MNL model can only describe preferences, here we can describe both

Table 4.5B. ***LC-MDCEV Second Stage Results***

	Segment 1		Segment 2		Segment 3	
Parameter	Utility	Satiation	Utility	Satiation	Utility	Satiation
Day Dependence – Category	**2.94**		2.44		1.68	
Time Dependence – Category	0.11		**-0.99**		0.29	
Day Dependence (Cat)* Log (Delay+1)	**-0.20**		**3.30**		-0.01	
Time Dependence (Cat)* Log (Delay+1)	0.03		0.06		**0.15**	
Day Dependence - Brand	**1.42**		**2.35**		**1.08**	
Time Dependence - Brand	**-1.76**		**-0.56**		**-0.65**	
Fat	**1.19**	**1.05**	**-0.33**	**0.18**	**0.59**	**-0.31**
Carbohydrates	**-1.12**	**-0.13**	**-1.09**	**0.35**	-0.05	**0.22**
Fiber	**1.23**	**-1.55**	**1.87**	**0.11**	**0.65**	-0.19
Protein	**-0.50**	**0.31**	-0.12	**0.90**	**-0.98**	**0.87**
BF	**4.60**	**1.24**	0.85	0.18	1.04	**0.25**
BL	0.18	-0.04	0.06	0.12	0.41	**0.86**
LD	-0.99	0.03	**0.77**	**0.32**	**1.17**	-0.02
PD	**-1.90**	-0.27	**-1.72**	**-0.56**	-0.57	**-0.52**
Weekend	-0.06	0.07	0.40	-0.58	0.68	-0.14

preferences and quantity choice in a joint model. In Table 4.5B, the first column shows the state-dependence, product characteristics and time of consumption effects for the first segment. We find that individuals are habitual in the choices made across consumption occasions at a given day part but across days. The results for across day choices agree with empirical research in discrete choice models. The individuals in this segment exhibit habituation in brand choice in day-dependence and variety-seeking in time-dependence variables. They also seem to prefer and consume higher quantities of items with fat, whereas seem to show less preference for carbohydrates. Most consumption for this segment happens during breakfast, and lowest consumption happens post-dinner.

4.5.4 Utility and Satiation Profile for Segment 2

The third column of Table 4.5A provides the utility and satiation parameters for the 'male and obese' segment (Segment-2). This group seems to prefer cakes, candy, chips, cookies, crackers and pastries over ice-cream. The preference for the rest of the categories is lower than that of ice-cream. They also seem to consumer higher quantity of cakes, chips, pastries and yogurt. This group also seems to prefer snacks that are considered unhealthy. However, they differ from the first group in terms of their tendency to seek variety within a day. From Table 4.5B, we see that they are less habituated in day-dependence term as well. They seem less likely to choose snacks with higher amount of fat and carbohydrates, but they do seem to consume more of the snacks with higher fat, carbohydrates. This segment seems to choose and consume (quantity) most of the snacks between lunch and dinner.

4.5.5 Utility and Satiation Profile for Segment 3

The third segment, whom we labeled as ‘young and active’ and the preference parameters are provided in Table 4.10A. We see that this segment of individuals seems to prefer breakfast bars and nuts over almost all other categories. They also seem to consumer higher quantities of these categories, along with yogurt, popcorn, others, cookies and crackers. They are more likely to choose categories that are considered healthy. This makes intuitive sense, as those who indulge in some level of physical activity might prefer consuming snacks that are healthier. The state-dependence parameters indicate habituation for the day-dependence parameter (category and brand), while this segment seems to be variety-seeking for the brand time dependence parameter. They seem to choose snacks that are high in fat, fiber, while less likely to choose snacks that are high in protein. Most of the snacking happens between lunch and dinner, while higher calories are consumed in the earlier part of the day, while post-dinner calorie consumption is lower.

By using the LC-MDCEV model, we get a better picture on the choices and quantity aspect of snack consumption. Given that quantity (calorie) consumption is one of the key variables that is of interest for researchers and policymakers, our results could provide new insights into how consumption is affected by different variables. Calorie consumption has been studied in marketing in different instances (Inman 2001; Khare and Inman 2009; Saksena and Maldonado 2017), but we are, to our knowledge, the first to provide a profile of various segments based on choices and calories consumed at the same time.

4.6 Discussion

In this study, we show that by using a latent class MDCEV model we could get a more nuanced set of segments compared to a latent class MNL model. We find that in both cases, a three-segment latent class model provides a superior fit. We include state-dependence terms to study the effect of prior choice on current choice within a day (time dependence) and the effect of snack consumed at a daypart on the choice made at the same day next day (day dependence). We also show that the LC-MDCEV model provides a better fit than a model which captures heterogeneity in consumers through a random effects model. To our knowledge, this is the first attempt to show how a latent class MDCEV model can be used to segment consumers into various groups based on choices and quantity consumption (satiation). Our results indicate that, the three segments differ in their preference for snacks both in terms of utility and satiation.

Table 4.6. *Calorie Consumption Profile by Segment*

	Mean and Standard Error (in parentheses)		
Category	old, overweight and inactive	Male and Obese	Young and Active
Ice-cream	139.93 (6.61)	153.06 (4.78)	140.91 (2.96)
Cakes	199.96 (9.11)	232.34 (24.06)	193.11 (11.71)
Candy	159.94 (4.99)	186.04 (4.88)	180.61 (5.29)
Chips	150.49 (2.17)	146.18 (1.95)	148.94 (2.10)
Cookies	166.82 (5.31)	163.85 (4.26)	160.75 (3.20)
Crackers	128.69 (4.38)	135.67 (5.82)	140.69 (3.57)
BF Bars	122.64 (4.03)	152.74 (8.01)	138.08 (4.50)
Nuts	181.59 (3.73)	187.12 (2.67)	191.89 (7.02)
Others	184.54 (11.85)	152.9 (9.34)	159.88 (8.02)
Pop Corn	139.66 (9.66)	178.5 (14.51)	119.73 (5.10)
Pastries	234.10 (8.48)	231.82 (5.86)	236.67 (5.72)
Pretzels	139.73 (7.65)	189.94 (16.97)	155.81 (9.54)
Puffs	153.53 (2.27)	155.53 (3.05)	154.49 (1.47)
Yogurt	125.21 (3.98)	121.19 (3.65)	137.01 (3.64)

In order to show the differences between the segments in terms of calories consumed, we provide the average calories (and the standard error) by segment in Table 4.11. We find significant differences in calorie consumption across the three segments by different categories.

The Segment-2 consists of individuals who seem to consume more calories across categories such as ice-cream, cakes, candy, popcorn and pretzels. Segment-3 consumes significantly higher amount of calories from yogurt and nuts compared to Segment-1. Similar differences can be seen across different categories by segment. Our approach makes a few contributions to the existing literature with regards to calorie consumption and preferences over categories. We incorporate satiation through calorie intake as an additional dimension to segment consumers rather than using a single dimension of preferences to segment consumers. With the MDCEV approach, we capture snacking behavior in a manner which is ignored under standard MNL formulation. Our data captures snacking behavior over a period of 14-days and consists of a sample that is representative of snack consumers, thus enabling us to generalize our results to a larger population. The advantage of this approach is that we can capture the unobserved heterogeneity in the sample in a better way compared to a random intercepts model, as seen by the superior fit provided by the LC-MDCEV model.

Our study has implications for both policymakers and marketers. Given that our segmentation approach generated three groups of consumers, policymakers can tailor any food related recommendations that suit the consumption patterns for each group. For the 'inactive' group, providing recommendations on reducing calorie consumption or communicating the need to indulge in some sort of physical activity can be an effective way to change their behavior. For the Segment-2, which consists mostly of male and obese consumers, we see that they seem to consumer more calories compared to the other groups from most of the categories. These consumers seem to be involved in some amount of physical activity but maybe compensating the energy spent through higher energy intake during snacks. Policymakers can communicate the need to either increase physical activity or not to reward themselves through higher consumption. Given the unique characteristics of each segment, policy interventions could be created to suit the needs of the three groups.

For marketing managers and researchers, our study provides a new perspective on consumption profiles of each segment. Marketers can use segment specific characteristics to encourage consumption and tailor snacks that cater to each group. By looking at preferences and satiation, marketers can create optimal package sizes that are targeted for each group of consumers. Marketers can also focus messages tailored to each group especially that encourage healthy snacking. By understanding consumption behavior and lifestyle choices, marketers can develop snacks that cater to the different groups. Our results also indicate that consumers display varying degree of variety-seeking and habituation across different segments While we do see that Segment-1 and Segment-3 are close in the habit and variety-seeking behavior, Segment-2 seems to differ from the others. Managers can use this information to associate different snack categories to different times of the day to encourage habituation. These messages could vary by segment as well. Consistent with prior literature (Inman 2001), Variety-seeking at brand-level indicates that marketers should provide variety in brands across categories.

We build on existing literature in multiple discrete-continuous choice models by addressing heterogeneity in consumers in a unique way. In a single model, we uncover preferences and satiation, that vary across segments. We show that consumers satiate at different levels across categories and segments. Since satiation itself is a function of various individual and product characteristics, managers and policymakers could use this information to increase or decrease calorie consumption (Galak et al. 2012). Our results indicate that any policy to increase or decrease calorie consumption should be built to suit the needs of each segment separately. As seen from the results, consumption varies by time of the day. Encouraging consumers to shift consumers from one part of the day to another through messaging could help reduce/increase consumption – an intervention that a policymaker or a manager can implement.

4.7 Conclusion

In this paper, using a latent class MDCEV, we attempt to uncover segments of individuals using a rich dataset that captures preferences and consumption. MDCEV model allows us to capture preferences and satiation in a joint model. This model gives a richer understanding of how consumers differ in the preference and satiation parameters across three segments. By allowing simultaneous consumption of snacks, which is a major relaxation of standard discrete choice model, we are able to depict choice behavior in an appropriate framework. Joint consumption of multiple quantities is a phenomenon that is observed in multiple fields (entertainment, stocks, vehicle-use). Using the MDCEV framework and applying the latent class literature to this model, we are the first to outline segments and delineate utility and satiation levels by various snack categories. Using a panel dataset, and by controlling for prior consumption, product, individual characteristics and time of the day effects, we provide a complete picture of snacking behavior. We also show how various segments differ in the degree of state-dependence between various snacks at category and brand level.

Our study does come with certain limitations. The MDCEV model assumes independence across consumption occasions (i.i.d. extreme value distribution), thus running into the familiar IIA problem that standard MNL model faces. This comes at the cost of computational ease, as more complex error structures that we attempted ran into convergence issues. This could be due to the limitations in the data and the large number of categories we have in our dataset. With a smaller number of snack categories, and a framework proposed by Kim et al. (200), one could address the IIA problem and account for complementary behavior that is common in snacking. Meal calories are also unobserved in our dataset. Any biases due to data collection or stock-outs are assumed away in our model.

With a focus on choice and quantity, we were able to uncover 3 latent segments in our dataset. We limit our model at category level choices, but there may be potential to uncover preferences at flavor or texture level. However, as the number of choices increase, the model suffers from convergence issues. Future research can look at ways to ease computational issues while handling potentially 1000s of flavors and textures in a single model.

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CHAPTER 5

CONCLUSION

In this dissertation, we study snack consumption through the framework of a multiple discrete-continuous choice (MDCEV) model. Marketing literature so far has used discrete choice models with a focus on choice of one alternative at an occasion such as grocery shopping. New developments in literature in economics and transportation fields have provided venues for exploring behaviors where consumers choose more than one alternative at an occasion and also make quantity choices at the same time. It is imperative that marketers study choices using models that can capture true behavior.

Using consumption data of individuals recorded through hand-held devices we are able to model consumers' choices from a variety of snack categories. In the second chapter, we separate the effects of satiation, intrinsic utility, and state dependence and control for the effect of covariates that affect each aspect. We find evidence of greater variety seeking in consumers at a brand level than at the category level within a day across time-periods. Further, we find that consumers category consumption choices across days are driven by habituation. We also find evidence that consumers experience satiation or diminishing marginal utility, and that satiation varies by snack categories and by dayparts. We estimate various specifications of the model and show that a dramatic improvement in model fit that can be achieved by including demographics, product characteristics and state dependence. We also estimate a model that includes all of these characteristics and account for unobserved heterogeneity. We show that this model provides a better fit than the base model. We then extend the MDCEV framework by using a gradient boosting algorithm from machine learning literature to predict alternatives that are part of a consideration set from which consumers make the final choice. Thus, we propose a new framework for modeling consideration sets in the MDCEV choice model framework. In prior literature, researchers constructed the consideration sets to study factors effecting consideration set formation in a two-stage choice model, using an enumeration. This method is computationally infeasible with more than ten choices in the universal consideration set. Instead, we propose a solution to reduce this complexity by using an ensemble method from the machine learning literature called XGBoost (extreme gradient boosting) algorithm. Using this algorithm, we predict the alternatives that a consumer is most likely to choose from, forming her consideration set. These consideration sets are constructed as a function of dayparts, prior choices and prior choices, allowing us to predict alternatives that vary across individuals and time of the day. We show that there the estimates of models that ignore consideration set formation are biased and by modeling consideration sets in the choice process, we reduce the bias. Using a rich panel data of individual level snack consumption, a setting where multiple discreteness and quantity choices play a role, along with groups of alternatives that are usually considered by individuals based on the time of consumption. Our setting enables us to estimate our model as the given number of alternatives are too large and individuals tend to choose from a smaller set of alternatives when snacking. We show that the proposed method provides a superior model fit by about 50% and reduces bias in parameter estimates compared to the base model. Using the proposed approach, we conduct two counterfactual experiments – changing time of consumption of a snack and switching a snack with another and estimate the change in calories consumed. We discuss implications for health policymakers and managers who are interested in implementing changes to snacks that could result in a decrease or increase in overall snack calorie consumption.

In the fourth chapter, we uncover latent segments of consumers who display homogenous snacking behavior using the individual level snack consumption data. Using a rich panel data of snack consumption, we first estimate a latent class model of consumer preferences using choice data alone. We estimate a model of choices and quantity consumption using the multiple discrete-continuous framework. We find that there are three distinct segments of snack consumers. We label them “old, overweight and inactive”, “male and obese” and “young and active”. To our knowledge, this is the first paper in marketing to show that satiation can also be used an additional dimension for customer segmentation apart from consumer preferences. We provide a better understanding and description of the differences in preferences and quantity consumption among distinct population segments.

We find that category consumption is governed by habituation across days in just one of three segments. Within a day, the “male and obese” segment seeks more variety in category consumption over the other segments. We find that all three segments are brand variety-seekers within a day while habituated across days for brand choices. We find that preference for each category varies across segments and satiation levels also differ across segments. We create profiles for the three segments and find that the calorie consumption varies significantly across the three segments varies by categories. Consumers in these three segments differ in their satiation levels by time of day, and product characteristics. Our results have implications for managers interested in creating optimal consumption bundles and for policymakers interested in addressing over-consumption leading to obesity among US consumers.

BIOGRAPHICAL SKETCH

Sriharsha Kamatham was born in Tenali, a coastal town in India but was brought up in Hyderabad, India. After completing his Bachelor of Technology at Regional Engineering College, Calicut in 2003, Harsha entered The Indian Institute of Technology, Madras. He successfully pursued a Master of Business Administration in Finance and Operations. He spent a decade with various firms in Bangalore, India and San Jose, CA. He joined the PhD program in Management Science in August 2015 at The University of Texas at Dallas.

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3. "Effect of Sentiment on Funding Success" (with Nanda Kumar and Parneet Pahwa, Published in *Journal of Business Research, May 2020*)
4. "Does Satiation's Effect Vary by Time of Day in Snack Consumption? A Nested MDCEV model" (with BPS Murthi and Marina Girju)
5. "Latent Segmentation of Snack Consumers: An Application of Multiple Discrete-Continuous Model" (with BPS Murthi and Marina Girju)

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