Consumer Food Choices and the Value of Time

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Gianna Short

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Advisers: Hikaru Peterson, Chengyan Yue

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The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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1 Preface

The foods we eat are a special class of commodities that we must physically consume and metabolize in order to live. Food differs from most other commodities in terms of associated preparation time, sensory appeal, and satiation limits. What we choose to eat has biological and health implications that do not apply to most other commodities. Wearing 100 pairs of shoes in a day might be excessive, but it is feasible. Eating 100 cheeseburgers in a day might not even be possible. Simply trying to eat that much would result in discomfort and ill-health. From a supply side perspective though, shoes and cheeseburgers are the same. Increased consumption means increased profits. Given our metabolic constraints on food intake, this can lead to a misalignment of incentives in the market.

Today's unprecedented rates of obesity and accompanying chronic health problems might be some of the outcomes of this incentive misalignment problem. Contemporary food availability seems inversely related to its nutritional quality. That humanity has learned how to produce such a steady and abundant food supply is a notable and welcome achievement. A consequence of this achievement, however, is that for many people, eating a healthy diet requires more time, effort, or money than buying cheeseburgers from a fast food dollar menu.

Intuitively, people understand that time—or lack thereof—plays a role in their food choices. Yet, time is often left out of consumer food choices modeled in economics. Imagine a shopper at the grocery store who needs to bring cookies to a party. He can choose pre-made cookies, refrigerated dough, a box of cookie mix, or ingredients to make cookies from scratch. How does he decide? Would his choice be different if the party was in an hour as opposed to tomorrow? What about a sale?

Next imagine at this party, a college student stands near the food table debating whether or not to eat a third cookie. They are delicious, and she would like more, but she does not want to lose her appetite for dinner. She also suspects that at the end of the party the host will give away the leftovers so she could take several cookies home if she waited. How does she decide?

These examples highlight two types of temporal-based economic decisions we make every day about food consumption. Both scenarios feature decisions related to opportunity costs. When considering opportunity costs, the man did not actually have four choices if the party was just an hour after his shopping trip. Pre-made would have been his only viable cookie option since the other three choices had opportunity costs of preparation time that he could not afford. For the college student, eating more cookies early-on meant less capacity for dinner. She faced an opportunity cost based on satiation as well as a risk that the cookies might be gone by the end of the party. As these examples motivate and Mincer (1963) pointed out, demand estimates can be biased when opportunity costs are ignored.

This dissertation seeks to gain improved insight about food consumption decisions by exploring their temporal nature. Part I approaches food and time from a behavioral economics perspective through an experiment designed to estimate the temporal discount rate for food consumption. Parts II and III are an in-depth exploration of how to incorporate the opportunity cost of time into food demand systems. The first approach (Part II) incorporates leisure time as a good into a complete demand system to eliminate the opportunity cost bias and estimate the elasticity of substitution between food and leisure. The second approach (Part III) develops and tests two methods to correct for the opportunity cost of preparation time using food purchase data alone.

Part I

Temporal discounting of food & the elusive present bias

2 Introduction

Why do we eat unhealthy diets despite the consequences? Obesity-related conditions include heart disease, stroke, type 2 diabetes and certain types of cancer, yet the prevalence of obesity in U.S. was 39.8 percent in 2015-2016 (Centers for Disease Control and Prevention, 2018). Overeating of unhealthy food is often thought of as an impulse control problem, and society holds the preconception that obesity rates are even higher at low incomes which can lead to paternalistic policy recommendations that reduce the agency and perceived rationality of target groups. In fact, there are actually complex differences in obesity rates by gender, race, and income that do not follow a predictable pattern (Centers for Disease Control and Prevention, 2018). Given obesity's prevalence despite people's best intentions, we clearly lack a robust understanding of its behavioral roots.

To explore self-control and impatience, experimental economic researchers have developed and refined a framework of intertemporal discounting experiments. The classic is a binary trade-off between "smaller sooner" and "larger later" rewards. These experiments generally ask participants to make choices regarding time-dated monetary rewards, and many have found a behavior pattern known as present bias.

Present bias can occur as the violation of one of two economic principles of intertemporal decision-making: stationarity or time consistency.[1] A "static preference reversal" is a violation of stationarity. Preferring \$10 now versus \$11 next week, but switching to prefer the larger sum if both payments are at two dates in the future (impatience for the amount *now*, but patience if all options are in the future). A violation of time consistency involves a "dynamic preference reversal." Patience if given the choice of \$10 in 52 weeks versus \$11 in 53 weeks, but then impatience if given the option to repeat the same choice a year later when the options would be \$10 at that time versus \$11 the following week.

Both static and dynamic preference reversals can result in present (or future) bias. Many earlier experiments have found evidence of present bias using an instrument known as a Multiple Price List (MPL) which contains questions like the preceding examples. However, innovations in experiment design have raised new questions regarding earlier findings. Many recent experiments have failed to find present bias as expected and sometimes find future bias instead (Andreoni and Sprenger, 2012a; Andersen et al., 2014; Olea and Strzalecki, 2014; Augenblick et al., 2015). As researchers seek to explain these findings, they often note that present bias is actually in reference to *consumption* utility rather than money. Since money is fungible and access to credit decouples it from consumption, money might not be adequate for testing intertemporal preferences of consumption.

While the perspective on monetary present bias is starting to shift, it is still generally assumed that present bias exists for intertemporal choices regarding consumption, especially food consumption which is full of visceral temptation that

[1] Stationarity requires the ranking of temporal rewards to only depend on the time distance and "payment distance" of the rewards. Time consistency requires that the ranking of temporal rewards at a pair of times does not change as the evaluation perspective gets closer to those times, i.e. a decision maker does not deviate from the original plan over time.

could lead to overeating. The intuition behind that rationale is strong, but very few temporal discounting experiments have used food despite the expected potential of present bias. Reuben et al. (2010) outlined several of the challenges involved including satiation, differing levels of desire for the food across individuals, additional uncertainty about future consumption desires, and limited divisibility potential of many foods.

Given the challenges of intertemporal experiments with food, I explored two methodological questions that contribute to the behavioral and experimental economics fields: (1) Can we assume temporal discounting behavior is the same for goods and money? (2) Do participants behave the same in hypothetical and in-person temporal discounting experiments? I also tested whether participants displayed a difference in discounting behavior based on childhood socioeconomic status (SES) as recent psychology studies have found correlations between low childhood SES and adult outcomes decades later (Poulton et al., 2002; Hill et al., 2016).

To explore these question, I adopted the Convex Time Budget (CTB) experimental framework developed and refined in Andreoni and Sprenger (2012a) and Andreoni et al. (2015). The CTB builds on a traditional MPL by adding a range of interior choice options in addition to the binary all-or-nothing corner solutions. By convexifying the budget set, the CTB allows a decision maker to potentially receive some of the reward both now *and* later.

I conducted an experiment in two rounds using popcorn, a snack food frequently eaten on impulse, as the primary good of interest. The first round was an in-person, incentive-compatible classroom experiment with popcorn. The second round was online with five different treatments including a monetary version serving as a comparison and robustness check. To my knowledge, this is the first CTB experiment conducted with a primary food reward, and it has illuminated a behavioral pattern of consumption smoothing that has not previously been discussed in this branch of literature.

Given the intuition that present bias and non-constant discounting behavior might be prominent in temporal food trade-offs, I had expected my results to indicate substantial present bias for food but not monetary rewards. However, in line with other recent experimental findings, only a small subset of participants (12 percent) displayed present bias for popcorn. A larger proportion (17 percent) actually had future-biased preferences for popcorn. For the sample in aggregate, there was no significant indication of present bias. There were also no significant differences or trends based on childhood SES. Discounting behavior was similar across the in-person and online hypothetical treatments, but was different for monetary and food rewards with many participants displaying consumption smoothing preferences for food rewards that were not seen with money rewards.

To gauge data quality and more deeply understand the choices participants made, I included a supplementary, decision-making "heuristic" question at the end of the experiment. Most participants' self-reported heuristic accurately described their choice behavior, confirming that participants understood the experiment. The majority of participants (62 percent) displayed a behavior pattern of interior choices that is observable using the CTB but would not have shown up on an MPL. They chose to receive allocations of approximately equal amounts over the two distributions. Less than 4 percent of participants indicated that they made choices based on getting popcorn at the soonest possible time, while 20 percent made choices to get the largest quantity.

The remainder of the article is organized as follows. Section 3 provides background on the theory and estimation strategy. Section 4 describes the experimental methods. Section 5 presents a summary of the experimental data. Section 6 contains estimation results, and Section 7 concludes with a discussion.

3 Theory and Estimation Strategy

In 1937, Samuelson published a short paper titled “A Note on Measurement of Utility,” in which he introduced a new model as a theoretical exercise. This model is now known as the canonical Discounted Utility (DU) model (Samuelson, 1937). As Frederick et al. (2002) pointed out in their review of the discounting literature, “Despite Samuelson’s manifest reservations about the normative and descriptive validity of the formulation he had proposed, the DU model was accepted almost instantly, not only as a valid normative standard for public policies...but as a descriptively accurate representation of actual behavior” (Frederick et al., 2002, pg. 351).

A key feature of the DU model is that all motives underlying intertemporal choice can be condensed into a single parameter: a constant discount rate.

$$U^t(c_t, ..., c_T) = \sum_{k=0}^{T-t} D(k) \cdot u(c_{t+k}) \tag{1}$$

$$\text{where } D(k) = \left(\frac{1}{1+\rho}\right)^k$$

Under the usual assumptions (completeness, transitivity, and continuity), intertemporal preferences can be represented as in Equation 1 with c as consumption in period t, and k as the delay length between time periods. $D(k)$ is a discounting function (here, exponential), and ρ is the constant discount rate. This utility representation relies on the two key properties of time separability and stationarity. Time separability implies that the marginal rate of substitution between any two time periods is independent of consumption in other periods and rules out habit formation. Stationarity implies that the marginal rate of substitution between any two consecutive periods is constant, hence the constant discount rate.

Given Samuelson's own caveats about this model,[2] it should not be surprising that virtually all the underlying assumptions have been empirically tested and found not to hold in at least some situations. Furthermore, Frederick et al. (2002, pg. 352) made the interesting point that many of "these anomalies are not anomalies in the sense that they are regarded as errors by the people who commit them." The field of behavioral economics seeks to find alternative models that can better account for these anomalies. Some of the most common alternative models of intertemporal choice (hyperbolic and quasi-hyperbolic discounting models) relax the stationarity assumption and accept the premise that the marginal rate of substitution between consumption in two periods might vary over the time horizon via a declining discount rate (Laibson, 1997). The DU model remains nested as a special case in the hyperbolic models.

The hyperbolic model represents violations of stationarity or time consistency (present bias) as part of a declining discount rate whereas the quasi-hyperbolic model has a separate parameter for present bias. Equation 2 represents the quasi-hyperbolic model with β as the present bias parameter and δ as a discount

[2]Samuelson (1937, pg. 155): [the model] is presented, not so much in the hope of furthering inductive investigation in these matters as of bringing out certain theoretical relations between the variables under consideration."

factor that could be constant or declining.

$$U^t(c_t, ..., c_T) = \sum_{k=0}^{T-t} D(k) \cdot u(c_{t+k}) \tag{2}$$

$$\text{where } D(k) = \begin{cases} 1 & \text{if } k = 0 \\ \beta\delta^k & \text{if } k > 0 \end{cases}$$

3.1 Multiple Price List (MPL) Experiments

The classic economic experiment to estimate intertemporal consumption preferences uses an MPL instrument which is fairly simple to create and administer. A simple two-period model assumes time-separability, linear utility, and stationary preferences. A participant chooses between a sooner payment c_t, and a later payment c_{t+k}, with utility function, $U(c_t, c_{t+k}) = u(c_t) + D(k) \cdot u(c_{t+k})$ where $D(k) = \delta^k$. Monotonically changing series of reward values and interest rates in the price list are designed to elicit a "switch point" where $u(c_t) \approx \delta^k u(c_{t+k})$. The price list switch point indicates approximately where sooner and later payments are equally valued. Under linear utility, $u(c) = c$ and δ is calculated as $(c_t/c_{t+k})^{1/k}$. An individual's discount rate can then be calculated as $\rho = (1/\delta) - 1$. This method can be used to compare rates for different goods or to test for the presence of non-constant discounting by varying the payment dates. However, it does not allow for parameter estimates of present bias.

Numerous studies have employed this methodology to examine monetary temporal discounting, but few economic studies have used MPLs to explore temporal discounting of food consumption. Among the few that have, Reuben et al. (2010) conducted an experiment on intertemporal choices of an actual food (chocolate) compared with money. The goal was to test whether discount rates would be the same between different goods, so the simple MPL was an effective instrument. The researchers found the average (one-week) discount rate for chocolate (28.77 percent) to be much higher than for money (5.46 percent) (Reuben et al., 2010). Olea and Strzalecki (2014) used a novel variation of the MPL based on annuities to estimate bounds for the parameters of both present bias and discounting for a hypothetical food (ice cream) compared with money. They did not find evidence for present bias in monetary rewards, and it was very weak for the hypothetical ice cream rewards. In fact, Olea and Strzalecki (2014) found indications of future bias.

A substantial drawback of the MPL on its own is that the assumption of a linear utility function can lead to upward-biased discount rates if the utility is in fact concave (Frederick et al., 2002). Perhaps in part for this reason, MPL experiments have tended to find high average discount rates. A second drawback is the possibility of participants displaying multiple switch points which violates the theoretical assumptions and makes parameter estimation invalid.

3.2 Double Multiple Price List (DMPL) Experiments

To correct for the upward bias of the linear utility assumption in the MPL, Andersen et al. (2008) developed a two-instrument solution to jointly estimate discounting and utility curvature parameters. They paired an MPL with the classic Holt-Laury risk instrument which has become known as a Double Multiple Price List (DMPL).

Ubfal (2016) conducted a set of development economics experiments in Uganda to compare discount rates across different foods for about 2400 subjects. The study used a hypothetical non-incentivized survey and an incentivized survey. The hypothetical survey used a DMPL adaptation assuming monotonicity to eliminate multiple switch points by design. That instrument allowed an estimation of the incidence of present bias finding a 12 percent prevalence of present bias in choices. The second experiment gave an additional survey to a random subsample of the participants who were told that one of their answers would be chosen at random and they would receive the food based on their choice. The researchers estimated discount rates for several different foods using the switch point equality between utility of sooner and later consumption. Ubfal (2016) interpreted higher discount rates for some foods as an indication that participants displayed higher impatience for those foods, specifically sugar, meat, and a starchy plantain.

3.3 Convex Time Budget (CTB) Experiments

Another experimental innovation came when Andreoni and Sprenger (2012a) developed a more parsimonious joint estimation strategy by convexifying the choice set and varying parameters to enable estimation based on one instrument known as the Convex Time Budget (CTB). The CTB uses a single experimental instrument with a convex choice set to jointly examine utility function curvature, discount factor, and present bias. Each participant divides a total allocation "budget" between two dates, c_t and c_{t+k}, subject to the convex budget constraint (Equation 3), where c is the amount of good, t is the initial allocation week, $1 + r$ is the gross interest rate, k is the delay length between allocation dates, and m is the total budget.

$$(1 + r)\, c_t + c_{t+k} = m \tag{3}$$

The CTB has several advantages over MPL and DMPL frameworks. The convex budget set contains more information than the binary choices in MPLs; it requires only one instrument; and the parameters of interest may be estimated precisely rather than with bounded ranges. The CTB allows participants to potentially have some of the reward both sooner and later. With monetary payments, this feature might have seemed unnecessary from a theoretical perspective. For an actual consumption good, though, the concepts of diminishing marginal returns and consumption smoothing potentially give this feature substantial importance.

A comparable use of the CTB framework comes from Augenblick et al. (2015) who conducted a set of experiments comparing the allocation of work effort in two different time periods with that of money using a CTB framework to generate point parameter estimates. They found virtually no evidence of present bias for monetary allocations. In the domain of work effort, they found an indication of present bias with participants allocating roughly 9 percent more work to the first work date if both dates are in the future.

Model specification For empirical experiments, utility can be specified with constant relative risk aversion as in Equation 4,

$$U(c) = \begin{cases} \frac{c^{1-\theta}}{1-\theta} & \text{if } \theta > 0,\ \theta \neq 1 \\ ln(c) & \text{if } \theta = 1 \end{cases} \tag{4}$$

and it can be represented in a simplified two period consumption model (Equation 5) by defining $\theta = 1 - \alpha$, with α as the utility function curvature, δ as the discount factor, and β as present bias with an indicator, n, that equals 1 if t is "now" (the present) for participants, and 0 if t is in the future (front-end delay).

$$U(c_t,\ c_{t+k}) = \frac{1}{\alpha}c_t^{\alpha} + \beta^n \delta^k \frac{1}{\alpha}(c_{t+k})^{\alpha} \tag{5}$$

By experimentally varying $1 + r$, t , and k, the CTB generates sufficient within-subject variation in choices to estimate point parameters for α, β, and δ. It is a simpler method than the DMPL for both participants and estimation, and has been quickly adopted. However, CTB has also been criticized in a few different ways leading to a lively debate in the literature.

Andreoni and Spregner also published a companion paper to Andreoni and Sprenger (2012a) in which they reported the results of experiments "On the Elicitation of Time Preference under Conditions of Risk" (Andreoni and Sprenger (2012b)). The use of CTB in studying risk preferences, in particular, has been the subject of substantial criticism (Epper and Fehr-Duda (2015), Cheung (2015)); however, it is not germane to the current study which does not focus on risk. A separate, relevant line of critique pointed out flaws in original CTB estimation strategy (Harrison et al., 2013). Cheung (2015) proposed a straightforward improvement: maximum likelihood estimation of the observed choice via multinomial logit which I adopt as the estimation strategy here.

Given the actual pair of allocations c_t and c_{t+k} chosen by the participants for each task, denoted as $U(*)$, the multinomial logit probability of the observed choice out of i different choices can be expressed as in Equation 6.

$$\Pr(U*) = \frac{exp(U*)}{\sum_i exp(U_i)} \tag{6}$$

The parameters α, β, and δ can be estimated using maximum likelihood. I estimated the model in R using the maxLik package specified with BFGS (Henningsen and Toomet, 2011). As a robustness check on the analysis, I also estimated parameters based on the results of several data consistency checks.

4 Experimental Methods

The first round was an in-person experiment (n = 36) that took place over a 4-week period using an actual food. Popcorn was chosen for the experiment since it is a low-cost, popular snack and is easily divided into different quantities. The use of food as the choice item contributes to the experimental literature in two ways. The first is a more accurate measure of intertemporal preferences since preferences represent the substitution between utility flows, not monetary payments. Most choice experiments use monetary rewards as a proxy for consumption of goods. Money serves as convenient proxy, but its suitability in this context has not been thoroughly examined. It it possible that temporal choice behavior for food is quite different than for money since many foods are not fungible over time and the desire for food (hunger) is definitely not. The second contribution is to provide a real-life incentive to avoid any hypothetical bias.

The second round was designed to expand the sample size and provide several robustness checks for the data. Round II was an online experiment with five treatments of 40 participants each (n = 200). The first treatment exactly replicated the parameters of the Round I experiment with a hypothetical story line that mimicked the in-person experience. Comparing this treatment with the Round I data serves as a check on the potential bias of both. Hypothetical bias might arise from the online participants not taking the experiment seriously since it was not incentive-compatible. Conversely, in-person bias might arise from uncontrollable specific circumstances of the experiment. Consistent results across these two samples strengthens the validity of both methods.

The maximum quantity of popcorn that participants could receive in Round I was a relatively small amount (4 cups) in order to keep the costs and distribution manageable for an in-person experiment. Since Round II was hypothetical, the second two treatments had maximum popcorn distributions of 8 and 16 cups respectively, keeping everything else the same. A monetary reward is unlikely to have an upper bound of desirability, but a food reward might have a saturation point. There is certainly an upper bound on the amount someone can eat in one sitting, and the hassle of carrying a large amount of popcorn home could outweigh its desirability. The 8 and 16 cup treatments were designed to observe if choice behavior varies with quantity and hits a saturation point.

The fourth treatment in Round II used chocolate instead of popcorn to check consistency of choices across different foods, and the fifth treatment used gift cards as a baseline for comparison with other studies.

4.1 Round I Methods

Recruitment – Participants were recruited for the experiment from an undergraduate Intermediate Microeconomics course at the University of Minnesota during the fall of 2016. All participants were 18 years or older and gave their consent to participate using a form approved by the University of Minnesota Institutional Review Board. The course professor introduced the experimenter to establish trust. Participants were likely to be in class at the same time every week, and they did not have to do anything outside of their normal routine to participate in the experiment. These factors (trust and normal routine) made the college classroom a suitable setting despite the well-known drawbacks of classroom experiments. The mid-semester regular classroom setting was also a way to control against the possibility that results might be compounded by different marginal utilities at different times.

Experimental Payments – Two key concerns in the experimental design were to eliminate the perception of risk regarding the payment of popcorn rewards and to ensure the equivalence of transaction costs for all payments.[3] The trust and daily routine of the college classroom setting served as good controls for both of these potential issues. These features of the experimental design minimized the potential that the results would confuse temporal preferences with risk preferences. All participants received a $20 cash payment in class for successful completion of the study at the end of the 4th week in addition to actual popcorn rewards (up to 4 cups of popcorn depending on participants' choices) in class.

Protocol – During the first week of the experimental session, participants were asked to complete 24 choice tasks on paper which I adapted from Andreoni et al. (2015).

Table 1 displays the conditions for each of the 24 choice sets, and Fig. 1 shows two choice sets from the experiment.

[3]Front-end delay is often added to all payments to equate transaction costs (Andersen et al 2008, Andreoni and Spregner 2012a).

Table 1: Variations in budget set parameters $(1+r)c_t + c_{t+k} = m$ for 24 choice sets where $m = 4$ cups of popcorn. $(1+r)$ is the "popcorn interest rate", t is the week of first distribution, and k is the week delay length between distributions.

choice set	1+r	t	k	choice set	1+r	t	k	choice set	1+r	t	k
a	1	0	3	e	1	1	2	i	1	2	1
b	$1\frac{1}{3}$	0	3	f	$1\frac{1}{3}$	1	2	j	$1\frac{1}{3}$	2	1
c	2	0	3	g	2	1	2	k	2	2	1
d	4	0	3	h	4	1	2	l	4	2	1
m	1	0	1	q	1	1	1	u	1	0	2
n	$1\frac{1}{3}$	0	1	r	$1\frac{1}{3}$	1	1	v	$1\frac{1}{3}$	0	2
o	2	0	1	s	2	1	1	w	2	0	2
p	4	0	1	t	4	1	1	x	4	0	2

TODAY *<u>and</u>* 3 WEEKS from today

	popcorn TODAY… & popcorn in 3 WEEKS	4 cups 0 cups	3 cups 1 cup	2 cups 2 cups	1 cup 3 cups	0 cups 4 cups
	Total cups:	4 cups	4 cups	4 cups	4 cups	4 cups
	Your choice:					

	popcorn TODAY… & popcorn in 3 WEEKS	3 cups 0 cups	2 ¼ cups 1 cup	1 ½ cup 2 cups	¾ cups 3 cups	0 cups 4 cups
	Total cups:	3 cups	3 ¼ cups	3 ½ cups	3 ¾ cups	4 cups
	Your choice:					

Figure 1: Example experiment choice sets.

Each choice had a maximum popcorn "budget" of $m = 4$ cups, and participants could choose how to allocate the popcorn budget between two different distribution weeks. The option to receive the full popcorn budget in the later distribution (and no popcorn in the sooner distribution) was always available. The 24 choices varied by the time interval between distribution weeks, $k \in (1, 2, 3)$; the date of the first distribution, $t \in (0, 1, 2, 3)$; and a varying "popcorn interest rate," $(1 + r) \in (1, 1.33, 2, 4)$. Subjects were informed that one of the 24 choices would be drawn at random and would be the actual popcorn allocations they received during the study to ensure that choices were incentive compatible. The incentive-compatibility mechanism does introduce a stochastic element into the experiment, but it is crucial to the design and does not vary across rounds or treatments. With an actual food item as the reward, payout for all 24 choice tasks would be logistically infeasible and almost certainly lead to oversaturation, obscuring the choice behavior of interest.

After subjects completed the CTB choice sets, they completed a questionnaire about their current hunger level and popcorn preferences. While subjects filled out the questionnaire, I used a randomly generated number to determine the popcorn payout choice (a-x) that would be binding for each participant and distributed popcorn to those subjects who were eligible to receive popcorn in the first week $(t = 0)$. I returned for the next three weeks on the same day and time. During the second and third weeks $(t = 1, 2)$, only popcorn was distributed. In the fourth week $(t = 3)$, I administered three other survey instruments in addition to distributing popcorn. The additional surveys included a demographic questionnaire, the Yale Food Addiction survey, and a subjective perception test. If all elements of the experiment were completed satisfactorily, subjects received a compensation of $20 for their time during the 4th week of the study in addition to the popcorn payouts they received.

To measure childhood SES, I utilized the same procedure as in Hill et al. (2016).

Participants used a scale of 1 to 7 to answer how much they agree (7) or disagree (1) with three questions.

1) My family had enough money for things growing up.

2) I grew up in a relatively wealthy neighborhood.

3) I felt relatively wealthy compared to others my age.

Each participant's responses for the three questions were averaged to generate a composite measure. The full sample was then divided into three groups based on cutoffs, "high childhood SES" for composites ≥ 5 , "mid childhood SES" between 3 and 5 (exclusive) and "low childhood SES" for ≤ 3.

Economists tend to favor revealed preferences (actual behavior) over stated preferences since the latter often tend to be biased (Loomis, 2011). However, in behavioral economics, since we do not expect people to always behave "rationally," then perhaps we can gain useful information by asking experiment participants to explain the reasoning behind their behavior.

Since allocation choices had been made in the first week, I was able to begin preliminary analysis before the final questionnaire was given in the fourth week. Many choice patterns were unexpected, and many appeared to be random. To gauge data integrity, I added the following additional, unplanned heuristic question to the demographic survey.

"Which best describes how you decided to answer the questions three weeks ago about the quantities of popcorn."

- *Pick the largest quantity*
- *Pick the soonest quantity*
- *Random*
- *Pick to make the distributions about equal*
- *Other* _________________________

The question was posed as multiple choice in order to make admitting random choices feel acceptable. The answer to this question will be considered the participant's "decision-making heuristic" and will help illuminate trends in the data.

4.2 Round II Methods

The second round of the experiment was an online hypothetical survey (n = 200) built with REDCap hosted at the University of Minnesota (Harris et al., 2009). The goals for round two were to investigate the two methodological research questions and to increase the overall sample size, especially for participants with low childhood SES.

Recruitment – Participants for Round II were recruited in the fall of 2017 using Amazon Mechanical Turk (AMT). AMT is an online, voluntary task-based labor market that is frequently used in social science research. Survey responses on AMT can be collected at a fraction of the cost of traditional data collection services, and Buhrmester et al. (2011) has found that sample populations on AMT are more representative than traditional classroom experiments. To ensure quality responses, participants were required to have a 95 percent approval rating within the platform as suggested by Peer et al. (2014). Location was restricted to the United States and participants could only complete a survey for each type of reward once. Potential participants were able to see a brief description of the study, the payment amount, and approximate duration (10 minutes) by browsing on AMT before they decided to participate. As with the in-person round, all participants agreed that they were 18 years or older and gave their consent to a form approved by the University of Minnesota IRB before the study began.

Experimental Payments – Participants were paid $0.50 upon successful completion of the survey through the AMT platform. The surveys were screened for data quality before approval and payment. I did not use specific attention check questions as they can backfire or lead to selection bias (Peer et al., 2014), but the survey did include several open-ended text questions where participants were informed that careless or nonsensical answers would be criteria for submission rejection and nonpayment.

Protocol – Round II used hypothetical scenarios designed to plausibly replicate the type of decision faced by the in-class participants of Round I so that results would be comparable. Since it was hypothetical, Round II participants could not receive actual popcorn, but the same incentive-compatible scenario as in Round I was built into the narrative. Instead of an experimenter visiting a classroom to give away free popcorn (Round I), the hypothetical narrative had a new store opening near the participant's workplace with the store owner stopping by to give free samples as a promotion. In the narrative, the store owner is not able to give samples to everyone on the same day so the participants fill out a survey with 24 questions regarding how to allocate their samples between two different possible days. They are told that one of their 24 choices will be drawn at random to be the samples they receive. Before the choice tasks began, participants chose specific details of the scenario (the name of the store and the name of the store owner) to encourage active engagement with the narrative. The REDCap survey software then dynamically filled in the details.

Five treatments of the Round II experiment survey were developed and conducted with 40 participants each. There were three popcorn treatments: one used the same quantities as in the Round I experiment ($m = 4$ cups), one used $m = 8$ cups, and one used $m = 16$ cups. The chocolate version used $m = 16$ individually wrapped 0.5 ounce chocolates,[4] and the gift card version had $m = \$12$. Gift cards were used as a proxy for money so that the same narrative would be plausible across all treatments.

To minimize the percentage of random responses, the decision-making heuristic question was included immediately after the choice allocations with additional follow up questions using branching logic. If participants indicated that they chose randomly, they were prompted with a reminder of the survey's purpose and given three options: (1) redo the allocation questions, (2) quit without compensation, or (3) indicate that random choices best reflected their preferences given the scenario. If participants made the latter choice, they were prompted to provide an explanation.

Demographic questions were the same as in Round I, with the scaled questions using a slider bar from 0 to 100 instead of the 1-7 scale. The Yale Food Addiction Survey and the subjective perception test were not included in Round II. The survey was deployed via AMT in small batches to vary the day of the week and time of day of responses.

[4]Described as "similar to those mini Halloween chocolates"

5 Data Summary

Table 2 displays age categories, gender, and race/ethnicity of participants in all four rounds. The Round II online samples are more diverse than Round I in terms of age, gender and race/ethnicity, though all samples tend to skew towards younger, white participants.

Table 2: Selected participant demographics across all rounds.

	Popcorn				Chocolate	Gift cards
	Small	Small	Medium	Large		
	In-person	Online				
Age						
Less than 35 years	36	21	21	23	26	25
35 - 49 years	0	12	15	10	12	11
50-64 years	0	6	4	5	2	3
65+ years	0	1	0	2	0	1
Gender						
Male	28	20	18	26	21	23
Female	8	20	22	14	19	17
Race/ethnicity						
White	29	32	26	34	34	30
Black	1	2	6	2	2	1
Asian/Other	5	5	4	2	3	7
Hispanic	1	1	4	2	1	2

5.1 Distribution of Childhood SES

Fig. 2 plots the distribution of childhood SES for the participants in the four popcorn treatments. The in-person Round I participants (circles) were the university students. In line with the common criticism of university-classroom experiments, the childhood SES measures of these participants tended to skew relatively high, with only three out of 36 participants being categorized as having had a low childhood SES. The in-person SES distribution was a motivating factor for completing the second round online. Participants from the online survey in the three popcorn treatments are shown with squares, triangles, and diamonds. These participants had a wider range of childhood SES. Combined, all four popcorn treatments generate a distribution with 31.4 percent of participants with low childhood SES, 41 percent mid childhood SES, and 27.6 percent with high childhood SES.

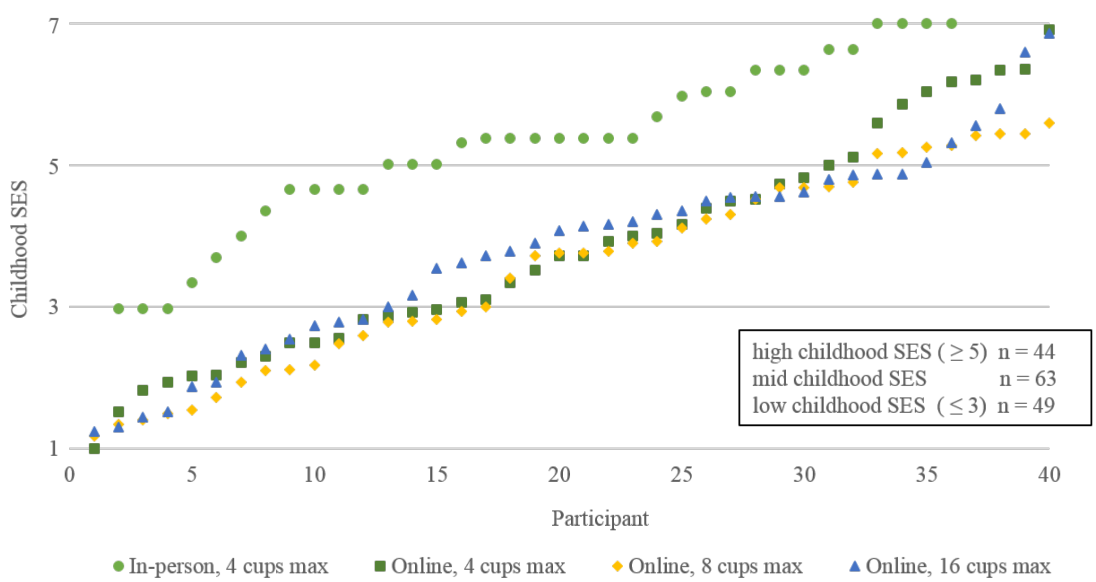

Figure 2: Self-reported distribution of childhood SES of participants in popcorn treatments.

5.2 Decision Behavior

Participant decision behavior is graphed in Figs. 3 through 5. Fig. 3 shows the aggregate behavior for all participants with popcorn rewards by treatment and whether the first distribution was immediate (solid bars) or had a front-end delay (pattern bars). The popcorn "interest rate," $(1+r)$, of the choice sets is shown on the horizontal axis, and the mean cups of popcorn allocated to the later distribution date (c_{t+k}) is on the vertical axis. The two treatments with small quantities of popcorn (4 cups max) are very similar which supports the comparability of the in-person and hypothetical methods. A consistent divergence of solid bars lower than pattern within a treatment would suggest present bias, but that is not the case for the aggregate sample.

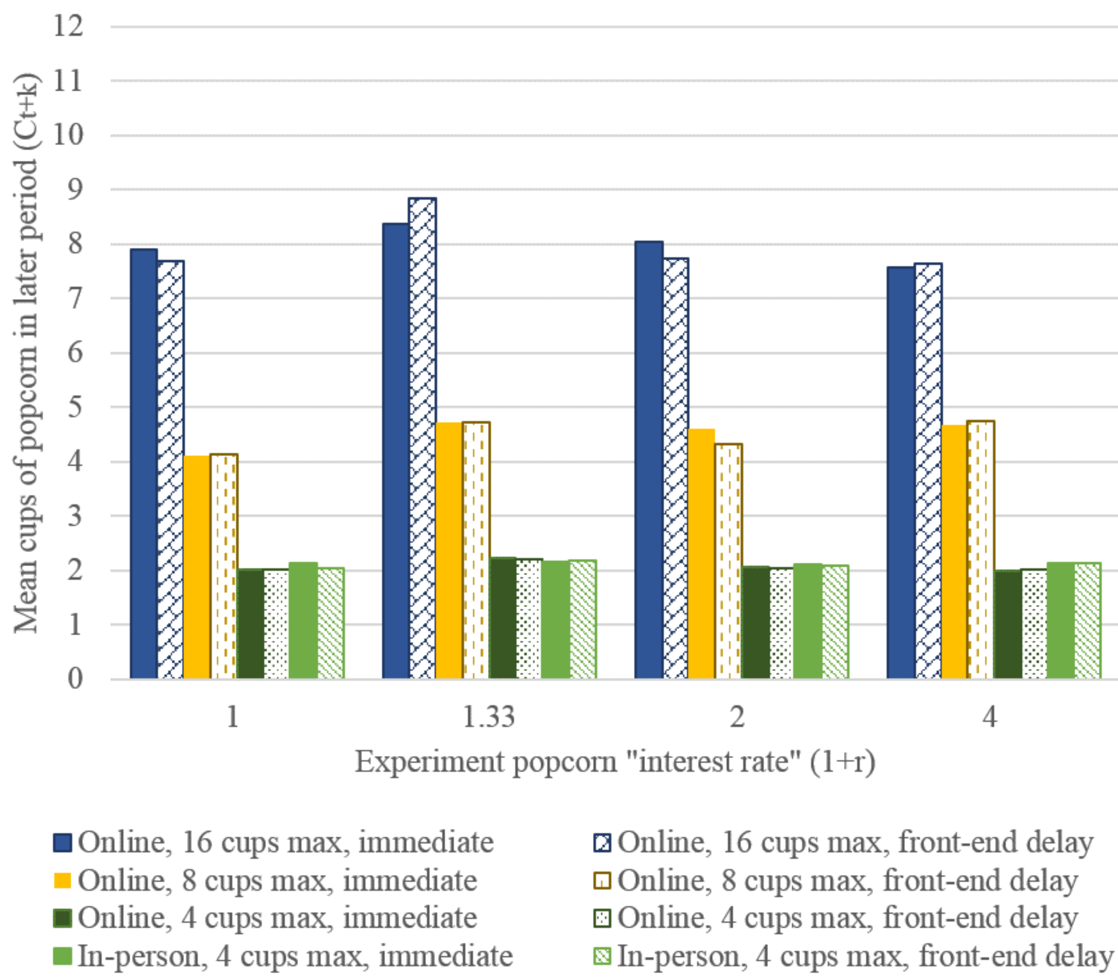

Figure 3: Mean cups of popcorn allocated to later distribution date (c_{t+k}) by front-end delay as a function of the gross interest rate $(1+r)$, n = 156.

Theory suggests that we should see an increase in mean popcorn allocations between rates 1 and 1.33. At rate 1, participants did not have to sacrifice quantity to get an early distribution of popcorn at c_t, but at 1.33, participants had to sacrifice some quantity of popcorn if they want to receive any in c_t. Fig. 3 shows that all treatments had a slight increase between 1 and 1.33 as expected. As higher interest rates, however, there is no consistent trend in mean cups at c_{t+k}. Each size treatment, had minor variation across interest rates with means around 2, 4.5, and 8 cups respectively for the small, medium, and large popcorn treatments. These approximate means are 53, 58, and 49 percents of the total popcorn available for rates 1.33, 2 and 4 if participants had chosen to receive all popcorn at c_{t+k}.

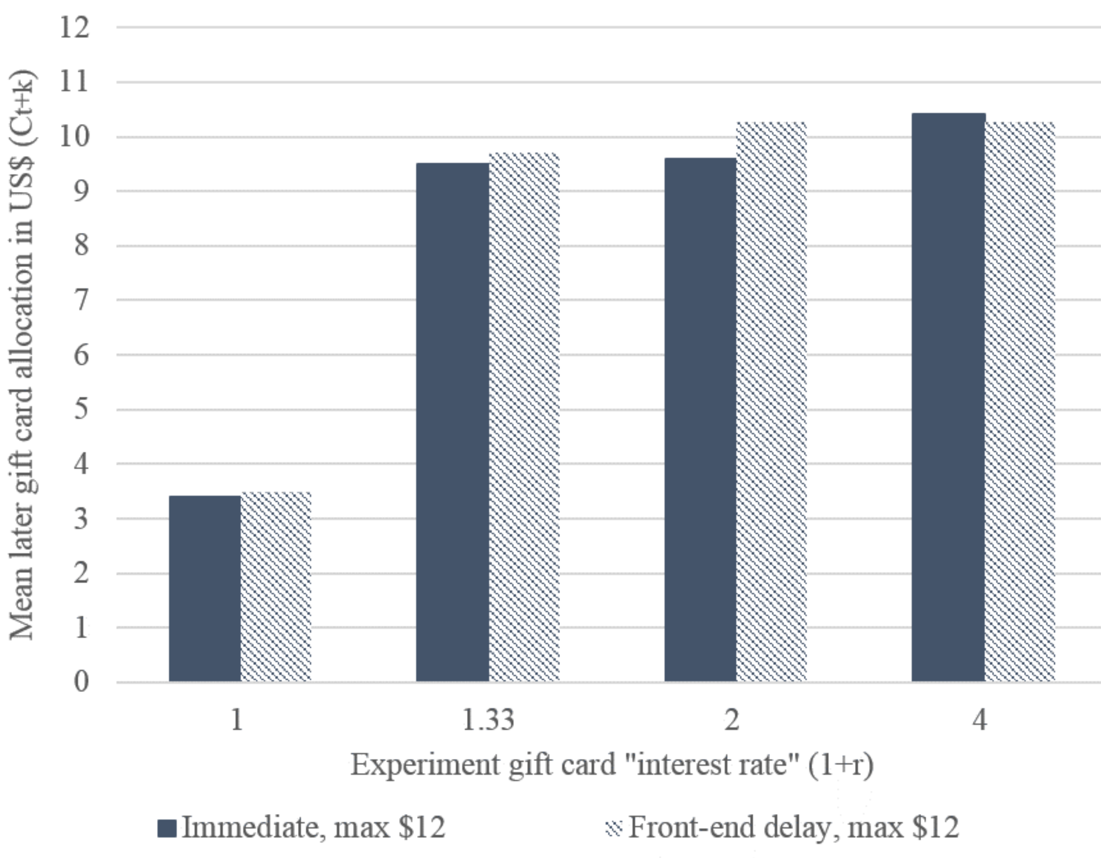

Figure 4: Mean gift card value allocated to later distribution date (c_{t+k}) by front-end delay as a function of the gross interest rate $(1 + r)$, n = 40.

In contrast, Fig. 4 displays the same type of graph for the gift card treatment. Here we see a very large increase in the mean allocations at c_{t+k} between rates 1 and 1.33 with a trend that continues to increase at higher rates. Visual inspection of Figs. 3 and 4 indicates different choice behavior for the gift cards compared with popcorn, but fairly consistent behavior on average for popcorn across the size treatments and online/in-person. In the gift card treatment, participants receive on average 83 percent of the value available for rates 1.33, 2 and 4.

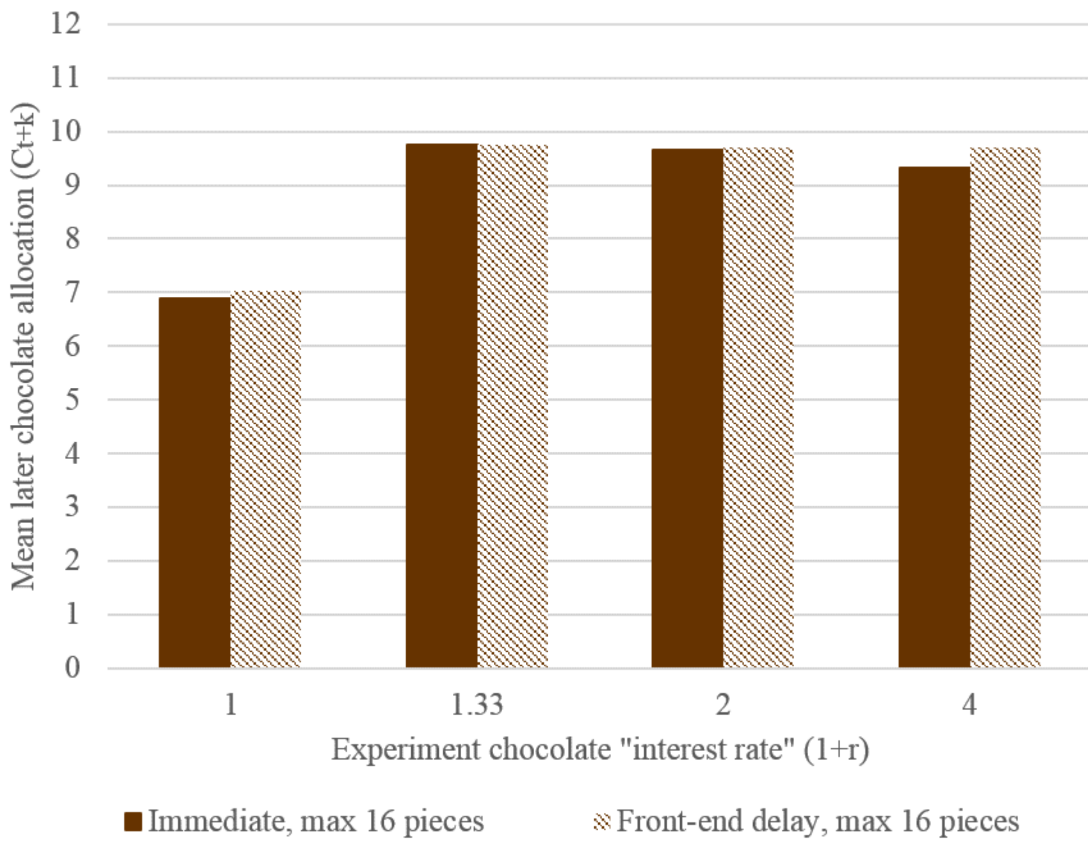

Figure 5: Mean pieces of chocolate allocated to later distribution date (c_{t+k}) by front-end delay as a function of the gross interest rate $(1 + r)$, n = 40.

The chocolate treatment served as a check on the possibility that behavior for popcorn might be anomalous. Fig. 5 displays the mean pieces of chocolate allocated to the later distribution date. The change in mean allocations between 1 and 1.33 is greater than for popcorn but less drastic than with gift cards. As the interest rates continue to increase, the behavior is similar to the popcorn treatments with participants receiving 61 percent of the value available at c_{t+k} for the rates 1.33, 2, and 4.

5.3 Decision-making heuristics

Table 3 lists the number of participants in each reward treatment broken down by their answers to the self-reported decision-making heuristic question. As suspected during the study, the in-person round had a fairly high percentage of participants who admitted they made decisions randomly (27.8 percent). Using the decision-making heuristic question with branching logic in the online version had the added benefit of greatly reducing the number of participants with random choices ($\leq$ 2.5 percent).

The data in Table 3 also support the hypothesis that carefully-designed hypothetical online experiments can reveal the same behavior as in-person, incentive-compatible experiments. If we look at the percent of participants in each heuristic for the in-person experiment excluding those who chose randomly (first column of the table), the percent of participants are comparable with all the other food-based treatments.

Table 3: Number of participants in each reward treatment by self-reported decision-making heuristic.

	Popcorn				Chocolate	Gift cards
	Small	Small	Medium	Large		
	In-person	Online				
About equal quantities	69.2%	62.5%	72.5%	62.5%	60.0%	10.0%
Largest quantity	23.1%	22.5%	25.0%	15.0%	37.5%	77.5%
Soonest quantity	0.0%	7.5%	2.5%	2.5%	0.0%	5.0%
Other	7.7%	5.0%	0.0%	17.5%	2.5%	5.0%
Random	*excluded*	2.5%	0.0%	2.5%	0.0%	2.5%
Total participants	26	40	40	40	40	40

The last notable feature of Table 3 is the difference in the heuristics between the five treatments with food and the gift cards. The majority of participants in every food treatment generally chose to make the distributions about equal while only 10 percent did so with gift cards. Most participants in the gift card treatment reported making decisions to get the largest quantity (77.5 percent). These self-reported heuristics reflect the choice behavior differences seen in Figs. 3 through 5.

Fig. 6 shows the aggregate popcorn choice behavior for the largest self-reported heuristic group, respondents who “picked to make the distributions about equal” (n = 97). There are two important implications we can see from this graph. The first is that the average behavior in the full sample (Fig. 3) is fairly similar to that of the “equalizers” in the 4 and 8 cup treatments: the mean cups allocated to the later distribution date remains relatively constant across interest rates at about half of the total amounts available. The 16 cup treatment in Fig. 6, however, shows an interesting downward trend between rates 1.33, 2, and 4. One goal of the different size treatments for popcorn was to determine if diminishing returns to consumption might make participants hit a popcorn “saturation point.” The second implication from this graph is that the downward trend might be an indication of such a saturation point for these participants.

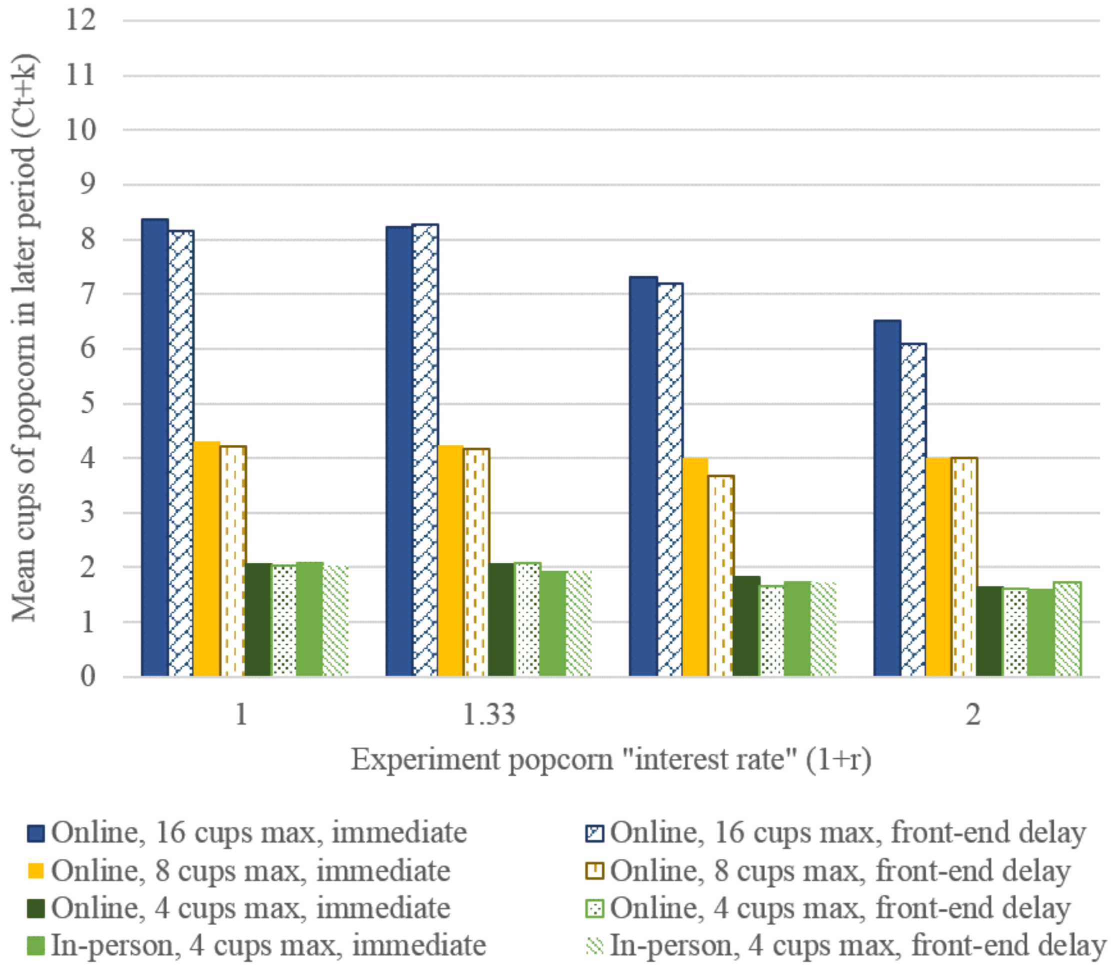

Figure 6: Mean cups of popcorn allocated to later distribution date (c_{t+k}) by front-end delay as a function of the gross interest rate $(1 + r)$ for participants with the decision-making heuristic "Picked to make the distributions about equal," n = 97.

5.4 Theoretical consistency checks

It is important to examine CTB experimental data for consistency with economic theory. By varying the experimental parameters, CTB experiments confront participants with intersecting budget lines providing the possibility for violation of revealed preference axioms as well as the assumptions of stationarity and time consistency. Chakraborty et al. (2017) analyzed the original Andreoni and Sprenger (2012a) CTB experiment as well as Augenblick et al. (2015) for three types of monotonicity violations and WARP violations. Most of the monotonicity violations they find are among people who make internal convex choices, and they wonder if this convex set of choices might be revealing something new that MPL experiments had not been picking up on before.

I performed three consistency checks that are comparable to the "demand monotonicity" and "impatience monotonicity" tests in Chakraborty et al. (2017). The basic idea in testing demand monotonicity or "adherence to the law of demand" is that holding t and k constant, an increase in $(1 + r)$ is equivalent to a decrease in the price of consumption in c_{t+k}. So, for two interest rates, r' and r'' such that and $r' < r''$, the c_{t+k} should be at least at large under r'' as under r' Balakrishnan et al. (2017). The experiment has 36 opportunities in which it is possible to violate this interpretation of the law of demand. Rates of violation of the law of demand are calculated per person with median rates are reported by heuristic group in Table 4.

Table 4: Median rates of participant consistency with economic theory in popcorn treatments by heuristic.

	About equal	Largest qty.	Soonest qty.	Other	Random	All
Median rate of violations of the law of demand	39%	0%	31%	6%	34%	25%
Median rate of present biased choices	11%	0%	33%	0%	22%	11%
Median rate of future biased choices	11%	11%	0%	0%	33%	11%
Number of participants	97	31	5	11	12	156

It is also possible to look for present biased and future biased choices directly. The experiment contains 9 pairs of choice sets with delay length and interest rate constant and with the early allocation date varying: either immediate or with a front-end delay. For example, we can compare the pair of choice sets that both have delay length of two weeks and gross interest rate of 1.33. What varies, is that the first choice set provides the possibility for popcorn immediately ($t = 0$) and the second choice set has a front-end delay ($t > 0$). If participants are present biased, then we expect to see them seek greater consumption in the early allocation of the immediate choice set compared to the front-end delayed choice set ($c_{t=0} > c_{t>0}$). Future biased choices are defined as the reverse ($c_{t=0} < c_{t>0}$). Rates of these present and future biased choices are calculated per person with the medians reported by heuristic group also in Table 4.

Participants who self-reported in the "about equal" group had relatively high rates of law of demand violations and a mix of both present and future biased choices. Sometimes both types of bias were seen within the same participant, but often participants veered one way or the other. Predictably, the 31 participants who reported the “largest quantity” heuristic (20 percent of popcorn participants) had perfect adherence to the law of demand and showed no present bias in their choices although some did show incidence of future bias. Also as expected, participants who indicated they primarily wanted the “soonest quantity” of popcorn had the highest rates of present biased choices. However, this was only 5 participants in the popcorn treatments (3 percent). The random heuristic group had relatively high rates of consistency violations on all three measures.

I used the data from the consistency checks to create an alternate set of groups to analyze for robustness. Participants who selected the random heuristic were removed to their own group. “Rational” participants had a perfect rate of adherence to the law of demand and no present or future bias. “Unbiased” participants had no present or future bias but did have violations of the law of demand. “Present biased” participants had at least one present biased choice and no future biased choices. “Future biased” participants had at least one future biased choice and no present biased choices. The rest of participants, named “Undefined,” have both present and future biased choices. Table 5 shows the overlapping classifications of popcorn treatment participants by heuristic and theoretical consistency grouping. While there are some obvious correlations (i.e. no future biased participants used the “soonest quantity” heuristic), there is not a clear mapping between the two types of classification.

Table 5: Classification of participants in popcorn treatments by heuristic and theoretical consistency grouping.

	Median rate of law of demand violations	Median rate of present biased choices	Median rate of future biased choices	Total participants
About equal quantities	39%	11%	11%	97
Largest quantity	0%	0%	11%	31
Soonest quantity	31%	33%	0%	5
Other	6%	0%	0%	11
Random	34%	22%	33%	12
All participants	25%	11%	11%	156

6 Estimation Results

Results from the multinomial logit maximum likelihood regressions for the pooled popcorn, gift card, and chocolate treatments are reported in Table 6. All parameter estimates are significantly different than zero at the 99.99 percent level, but given the model, the more appropriate measure is if the estimated parameters are different than one. If $\beta = 1$, the model implies no present bias. A parameter value of $\beta < 1$ would indicate present bias, and $\beta > 1$ would indicate future bias. Examination of Table 6 reveals that none of the reward types show any indication of present or future bias for the full samples in aggregate. Popcorn has $\beta = 1.01$, chocolate has $\beta = 1.00$, and gift cards have $\beta = 1.00$. All three rewards do have discount factors which are similar across reward type $\delta \in (0.88, 0.91)$. The biggest difference across reward types is that the utility curvature parameter is slightly risk seeking for the gift cards with $\alpha = 1.03$, whereas it is 0.53 for popcorn and 0.69 for chocolate.

Table 6: Parameter estimates using multinomial logit maximum likelihood for utility curvature (alpha), present bias (beta), and annual discount factor (delta), all treatments, by reward type.

	Parameter	Estimate	Std. error	t value	Pr(> t)	LB 95% CI	UB 95% CI
popcorn n=156	α	0.53 †	(0.01)	64.28	<2e-16 ***	0.51	0.54
	β	1.01	(0.04)	28.58	<2e-16 ***	0.94	1.08
	δ	0.91 †	(0.01)	71.39	<2e-16 ***	0.88	0.93
chocolate n=40	α	0.69 †	0.01	60.32	<2e-16 ***	0.67	0.71
	β	1.00	0.04	24.92	<2e-16 ***	0.92	1.08
	δ	0.88 †	0.01	61.53	<2e-16 ***	0.85	0.91
gift cards n=40	α	1.03 †	0.01	116.27	<2e-16 ***	1.01	1.05
	β	1.00	0.03	39.12	<2e-16 ***	0.95	1.05
	δ	0.91 †	0.01	96.50	<2e-16 ***	0.89	0.93

0 '***' 0.001 '**' 0.01 '*' 0.05 † = significantly different than 1

Table 7 reports estimates by theoretical consistency grouping for all popcorn treatments. Here we do see significant present bias ($\beta = 0.76$) for the group that we know made consistently present biased choices ($n = 17$). However, we also see definitive future bias ($\beta = 1.39$) from the future biased group which is larger ($n = 25$).

Finally, Table 8 reports parameter estimates by childhood SES excluding the "random" heuristic group. In general, there was only a small degree of (non-monotonic) variation in parameters across the groups, so we are not even able to consider trends. Utility curvature is similar for all groups with $\alpha \in (0.49, 0.55)$. Present or future bias is not found to be significant in these aggregate groups with $\beta \in (0.99, 1.06)$, and all also have fairly similar discount factors $\delta \in (0.90, 0.934)$.

Table 7: Parameter estimates using multinomial logit maximum likelihood for utility curvature (alpha), present bias (beta), and annual discount factor (delta), popcorn treatments by theoretical consistency groupings.

	Parameter	Estimate	Std. error	t value	Pr(> t)	LB 95% CI	UB 95% CI
rational n=24	α	0.73 †	(0.02)	36.04	<2e-16 ***	0.69	0.77
	β	1.02	(0.06)	15.53	<2e-16 ***	0.89	1.15
	δ	1.07	(0.03)	35.81	<2e-16 ***	1.01	1.13
unbiased n=32	α	0.55 †	(0.01)	44.11	<2e-16 ***	0.53	0.58
	β	1.03	(0.05)	19.10	<2e-16 ***	0.93	1.14
	δ	0.93 †	(0.02)	47.02	<2e-16 ***	0.89	0.97
future biased n=25	α	0.47 †	(0.02)	23.51	<2e-16 ***	0.43	0.51
	β	1.39 †	(0.14)	10.07	<2e-16 ***	1.12	1.66
	δ	0.89 †	(0.03)	25.34	<2e-16 ***	0.82	0.95
present biased n=17	α	0.39 †	(0.02)	17.94	<2e-16 ***	0.35	0.43
	β	0.76 †	(0.10)	7.47	<2e-16 ***	0.56	0.96
	δ	1.05 †	(0.05)	19.35	<2e-16 ***	0.94	1.15
undefined n=58	α	0.52 †	(0.02)	33.43	<2e-16 ***	0.49	0.55
	β	0.97	(0.06)	15.73	<2e-16 ***	0.85	1.09
	δ	0.90 †	(0.02)	39.62	<2e-16 ***	0.86	0.94
random n=12	α	0.53 †	(0.05)	11.27	<2e-16 ***	0.44	0.62
	β	0.78	(0.20)	3.96	<2e-16 ***	0.39	1.16
	δ	0.55 †	(0.07)	8.22	<2e-16 ***	0.42	0.68

0 '***' 0.001 '**' 0.01 '*' 0.05 † = significantly different than 1

Table 8: Parameter estimates using multinomial logit maximum likelihood for utility curvature (alpha), present bias (beta), and annual discount factor (delta), popcorn treatments by childhood. SES.

	Parameter	Estimate	Std. error	t value	Pr(> t)	LB 95% CI	UB 95% CI
all n=144	α	0.52 †	(0.01)	61.94	<2e-16 ***	0.50	0.53
	β	1.02	(0.04)	27.68	<2e-16 ***	0.95	1.10
	δ	0.92 †	(0.01)	69.26	<2e-16 ***	0.90	0.95
low n=46	α	0.49 †	(0.02)	32.82	<2e-16 ***	0.46	0.52
	β	1.06	(0.07)	15.23	<2e-16 ***	0.93	1.20
	δ	0.93 †	(0.02)	38.27	<2e-16 ***	0.88	0.97
mid n=56	α	0.51 †	(0.01)	38.88	<2e-16 ***	0.48	0.53
	β	0.99	(0.06)	17.53	<2e-16 ***	0.88	1.11
	δ	0.94 †	(0.02)	44.07	<2e-16 ***	0.90	0.99
high n=42	α	0.55 †	(0.02)	34.13	<2e-16 ***	0.52	0.59
	β	1.02	(0.07)	14.62	<2e-16 ***	0.89	1.16
	δ	0.90 †	(0.02)	35.88	<2e-16 ***	0.85	0.94

0 '***' 0.001 '**' 0.01 '*' 0.05 † = significantly different than 1

7 Discussion

The experiment's results did not support the intuition of strong present bias in intertemporal food consumption decisions. Rather, the results are fairly consistent with other recent findings that indicate many people exhibit constant discounting, some people display present bias, and some people actually display future bias. Additionally, the data revealed that a majority of experimental participants preferred to make the allocations of food about equal on the two distribution days. This "consumption smoothing" behavior is especially notable since it is not feasible in the more traditional MPL experiments. The convex choice set of the CTB allows for interior choices, whereas the binary choice set of an MPL typically uses all or nothing choices in the two time periods. The gift card treatment of this experiment showed that interior choices are less preferred for monetary rewards than for food rewards, and the economic logic underlying the monetary behavior is perhaps why interior choices have been overlooked until recently.

A growing body of evidence suggests that for many people, high rates of present bias and discounting are artifacts of experimental design with the implicit risk of future rewards affecting decisions to favor present choices. Halevy (2015) found that this explanation was relevant for 10 percent of participants who held time consistent but non-stationary preferences. As experimental designs have better controlled for this perception of risk, the rates of present-biased findings have decreased (Andersen et al., 2014; Andreoni and Sprenger, 2012a).

My results bring up another potential piece of the experimental design puzzle: perhaps people are less likely to display present-biased consumption if they are presented with convex choices. There could be an additional component of utility derived from rewards on multiple days, perhaps related to the behavioral theories of anticipation utility or loss aversion. This hypothesis is testable in future research by replicating this experiment with binary MPL choices in addition to CTB for the same participants or properly randomized samples.

To extend this idea, consider an early study of food-related impatience conducted by Read and van Leeuwen (1998). Unaware that they were participating in an experiment, subjects were approached in their workplaces and offered a choice of snack foods to be delivered a week later. Some choices were healthy and others were not. A week later, the experimenters returned and offered subjects the same choice again to be delivered immediately. Many participants who had originally made healthy snack choices in the advanced decision switched to unhealthy choices in the immediate decision. Very few participants made the reverse switch. Perhaps if the researchers had offered their subjects choices that involved mixtures of healthy/unhealthy snacks, those interior choices would have been preferred and fewer people would have switched their choices.

A challenge with evaluating results in the temporal discount literature as a whole is that familiar concepts like "impatience" can be interpreted in many different ways. Impatience can refer to present bias violations of stationarity and time consistency when people make preference reversals to favor immediate consumption. Or it can also refer to the relative steepness of discounting between goods as in Ubfal (2016) who found that people are more impatient (i.e. discount the future more steeply) for several types of food in particular. Yet another alternative is that impatience could simply be considered the inability to delay gratification as in the "Marshmallow Tests" of Shoda et al. (1990) and Watts et al. (2018).

Regardless of its nuances, the intuition behind impatience is strong since most people feel it in their daily lives, and it is certainly possible to contrive experimental scenarios where people exhibit impatience in ways that contradict the classical DU model. However, we are now also seeing experimental scenarios where behavior contradicts the very models introduced to explain the original contradictions. In the context of this moment it is important to acknowledge the inherent simplifying nature of our economic models and try to incorporate differing perspectives. The incorporation of the heuristic question has opened a new line of inquiry.

Part II

Full-income demand system with leisure

8 Background

In the preface to her pioneering 1934 book "The Economics of Household Production," Margaret Reid noted, "with few exceptions the interest of economists has been concentrated on that part of our economic system which is organized on a price basis. The household is an integral part of our whole economic system. Only if it is viewed in this way can we become aware of the labor costs and productive activities necessary to maintain present standards of living" (Reid, 1934, pg. v). She reports that time spent on housework increases non-proportionally with family size since it is subject to the ultimate constraint: 24 daily hours. "Increased time given to homemaking is, to a large extent, drawn from the housewife's leisure. There is thus a definite limit on the time which can be given. As this limit is approached the standard tends to change: unessentials tend to be eliminated and certain things are bought rather than made" (Reid, 1934, pg. 103).

The extent of household production in the U.S. has changed dramatically since Reid's time. She frequently cited clothing-making as in integral household production activity, yet it has been completely outsourced from household production today. Food preparation, however, has somehow managed to remain a component of modern household production for the vast majority of Americans. Advances in cooking technology, food science, and the increase in options for food prepared outside the home have made food preparation easier and less time consuming than it used to be, but the average American still spends 37 minutes a day in food preparation and cleanup (Hamrick, 2016). Food preparation is also still a larger draw on women's leisure than men's. On average in 2014, women spent 51 minutes on food preparation and clean up whereas men spent 22 minutes (Hamrick, 2016).

Given the persistence of food preparation in modern household production, we must take it into account in our efforts to characterize economic systems–especially food demand systems. Two decades after Reid's book was published, Mincer (1963) formalized the core theoretical underpinnings of the opportunity cost of time. The main idea is that the properly defined price that a consumer faces is not the market price p, but rather $p + c$ where c is the opportunity cost of time. Even if the prices are fixed in cross section, the opportunity costs of time are not. If the opportunity costs are a function of the wage rate, their omission will bias the parameter estimates. Becker (1965) expanded the study of opportunity costs and developed the household production model incorporating the value of time into the income constraint. Later, Gronau (1977) formalized the theory of the trichotomy of market work, home production, and leisure.

The foundations set by Mincer, Becker, and Gronau led to the development of a body of literature regarding the the relationship between time and food (e.g. Prochaska and Schrimper, 1973; Redman, 1980; Blundell and Walker, 1982; McCracken and Brandt, 1987; Browning and Meghir, 1991; Alderman and Sahn, 1993; Byrne et al., 1996; Nayga, 1996; Park and Capps Jr., 1997; Aguiar and Hurst, 2005, 2007; Hamermesh, 2007; You and Davis, 2010; Huffman, 2011a; Liu et al., 2012; Gelber and Mitchell, 2012). The general conclusion across these studies is that as the opportunity cost of time increases, at-home food consumption decreases while away-from-home food consumption increases (Davis, 2014). More nuanced conclusions have been rather limited by data, since there is no sampling unit complete data set that contains both time use and disaggregated expenditures on food purchases for the same households.

The data landscape has improved somewhat with the implementation of the American Time Use Survey (ATUS) which began in 2003 and has continued annually since then. Many researchers have analyzed the ATUS data with particular attention to food (Mancino and Newman, 2007; Lo and Tashiro, 2011; Davis, 2014; Hamrick, 2016), but the gap linking time use with expenditures remains. With ideal data, a natural course of study would be to use the "simple neoclassical model of labor supply" by adding leisure as a good in a demand system with a budget that accounts for both monetary and time constraints (Deaton and Muellbauer, 1980b). One rare study by Alderman and Sahn (1993) was able to estimate a version of this model using a small survey in Sri Lanka that did actually contain information on time use and food expenditures.

The primary drawback to not including the opportunity cost of time in a demand system is that as Mincer (1963) outlined, neglecting opportunity cost of time in demand system estimates can lead to bias. Davis and You (2010) found that the time cost of food preparation can range from 30-49 percent of the total cost associated with eating, so the potential for bias is substantial. However, given that we do not yet have time use and expenditures in U.S. data, two economic approaches have been generally used to incorporate the value of time in food purchasing decisions. The first approach encompasses studies based on demand system estimation that either endogenize or condition on a value of time (e.g. Browning and Meghir, 1991; Park and Capps Jr., 1997; Capps Jr. et al., 1985; Liu et al., 2012; Okrent and Kumcu, 2016). The second approach uses a household production framework (e.g. Prochaska and Schrimper, 1973; McCracken and Brandt, 1987; Nayga, 1996; Byrne et al., 1996; Aguiar and Hurst, 2005, 2007; Hamermesh, 2007; You and Davis, 2010; Gelber and Mitchell, 2012). A recurring finding in these studies from both approaches is that the likelihood of outsourcing food preparation increases as the opportunity cost of time increases.

Parts II and III of this dissertation implement two new ways to incorporate the opportunity cost of time into demand system estimates focusing on demand for food at home. In Part II, I used a demographic cohort matching technique similar to that used by Hamermesh (2007), Aguiar and Hurst (2005), and Aguiar and Hurst (2007) to link national ATUS time use estimates with Nielsen expenditure data provided by the Kilts Center for Marketing at the University of Chicago Booth School of Business. I then used those composite data to estimate a full-income demand system with both goods and leisure.

9 Theory

Deaton and Muellbauer (1980b) outlined the simple "neoclassical model of labor supply" which is an intermediary between the neoclassical model of demand and the household production model. A key addition is that the income variable is redefined to mean "potential" income if all available hours are spent working (zero leisure). Thus the price of leisure (opportunity cost) is assumed to be the foregone wage rate.

However, time can also be spent in "home production," i.e. food preparation. Time spent in food preparation is neither leisure (for most people) nor market work.

9.1 Model set-up

To set up the model, I derive a simple neoclassical model of labor supply for wage-earning, single-headed[5] households to build a complete demand system including at-home food grouped by preparation time (high preparation and low preparation), food away from home, all other goods and services, and leisure.

Definition of variables Utility is a function of the consumption of goods q_k and leisure t_l.

$$u = U(q_{HP}, q_{LP}, q_{FAFH}, q_{AOGS}, t_l) \tag{7}$$

v	non-labor income	T	time endowment
wt_w	labor income	t_w	market work hours
w	market wage rate	t_l	leisure hours
p_k	price of good k	t_h	housework hours
q_k	quantity of good k $\quad q_k \geq 0$		where T, t_w, t_l, $t_h \geq 0$
$k \in$	{HP: high preparation food at home,	Q_i	goods q_k and leisure t_l
	LP: low preparation food at home,	$i \in$	$\{q_{HP}, q_{LP}, q_{FAFH}, q_{AOGS}, t_l\}$
	FAFH: food away from home,		
	AOGS: all other goods and services}		

[5]As Alderman and Sahn (1993, pg. 876) pointed out, "leisure is far less fungible than goods, and hence it is more necessary that its consumption be indexed." A demand system for dual-headed households should include separate time variables for each person, but assigning a price for each person's time separately either requires untenable assumptions or causes multicollinearity issues in the current study.

Leisure is treated just like goods with price as the wage rate. The time endowment, T, is the sum of time spent in market work, home production work (which includes food preparation), and leisure. It is defined as 24 hours per day less "maintenance time" (which includes sleep).

$$T = t_w + t_l + t_h \tag{8}$$

In the most simple specification of the model, t_w, t_l, and t_h are assumed to have the same price for a consumer (the individual's wage rate). Thus, spending time in leisure or housework carries the opportunity cost of forgoing market work that can vary across consumers.

Full income budget constraint The adding-up condition implies that a person uses all money income (non-labor and labor) on goods (Equation 9.

$$m \equiv \Sigma p_k q_k = v + w t_w \tag{9}$$

However, the consumer is assumed to have a time constraint in addition to the budget constraint. Since working time (t_w) does not enter the consumer's utility function, we can rearrange equation 8 to solve for t_w and substitute it into equation 9 to get the "full-income" constraint (Equation 10).

$$\begin{aligned} v + w(T - t_h - t_l) &= \Sigma p_k q_k \\ v + wT &= \Sigma p_k q_k + w t_h + w t_l \end{aligned} \tag{10}$$

Full-income is defined as M (Equation 11).

$$M \equiv v + wT \tag{11}$$

$$M = \underbrace{v + wt_w}_{\text{money income}} + w(T - t_w)$$

Full income M is equal to money income m plus the opportunity cost of non-working time $w(T - t_w)$. A key implication of full income is that change in the wage rate has effects on behavior beyond a change in the price of a good. This alters analysis of income and substitution effects, although Huffman pointed out that "the income effect on demand can be represented either by non-labor income (v) or as full income [M], given that w, which is the opportunity cost of time, is held constant in either case" Huffman (2011b, pg. 5).

Full cost function The full cost function is defined by the consumer choosing q_k and t_l to minimize the full-income constraint subject to maintaining utility u (Equation 12). Home production time (t_h) is embedded in the choices of q_k and t_l. It does not appear in the utility function but is present in the budget constraint since it limits the amount of time that can be spent in leisure and also has the wage-rate opportunity cost.

$$c(u, w, p) = \min_{q_k, t_l} \{\Sigma p_k q_k + w(t_h + t_l);\ u = v(q_k, t_l)\} \tag{12}$$

With utility maximization, $c(u, w, p) = M$. Since time variables are treated as goods with wage as the price, the cost function shares all properties of normal cost functions. Maximum attainable utility is $\psi(v + wT,\, w, p)$.

Hicksian demands	Marshallian demands
$q_k = h_k(u, w, p) = \frac{\partial c(u,w,p)}{\partial p_k}\ \forall i$	$q_k = g_k(v + wT,\, w, p) = g_k(M, w, p)\ \forall k$
$t_l = h_l(u, w, p) = \frac{\partial c(u,w,p)}{\partial w}$	$t_l = g_l(v + wT,\, w, p) = g_l(M, w, p)$

9.2 Slutsky substitution equations and elasticities

To examine income and substitution effects and how the use of full-income changes things, we can examine the Slutsky equations. The Slutsky equation *with respect to prices of the goods* takes the usual form, but the Slutsky equation *with respect to the price of time (wage rate)* contains an additional term: a "revaluation of time endowment effect" which is positive for normal goods (Deaton and Muellbauer, 1980b, pg 91).

Let Q_i stand for any good q_k or leisure t_l.[6] The Slutsky substitution equation for any good or leisure with respect to the price of a good is represented in Equation 13, and with respect to wage in Equation 14).

$$\frac{\partial Q_i}{\partial p_k} = \underbrace{\frac{\partial Q_i}{\partial p_k}\,|_u}_{(+\,|\,-)} - \underbrace{q_k \cdot \frac{\partial Q_i}{\partial M}}_{(+)} \tag{13}$$

$$\frac{\partial Q_i}{\partial w} = \underbrace{\frac{\partial Q_i}{\partial w}\,|_u}_{(+\,|\,-)} - \underbrace{t_l \cdot \frac{\partial Q_i}{\partial M}}_{(+)} + \underbrace{T \cdot \frac{\partial Q_i}{\partial M}}_{(+)} \tag{14}$$

[6] Since t_h does not appear in the utility function, it is left out of subsequent equations.

The left-hand-side terms in both equations are derived from the Marshallian uncompensated demands. The first term on the right hand side in both Slutsky equations (the “substitution effect”) is derived from the compensated Hicksian demands. The substitution effect is expected to be negative for all goods and leisure when $i = k$ in accordance with the law of demand. A negative (positive) compensated demand term is also expected when i and k are complements (substitutes).

The second term on the right hand side in both equations is analogous to the standard “income effect.” However, it is technically a “full-income effect” via equation 11. Since t_l can not be negative and the consumption of all goods including leisure is expected to increase as full income increases ($\partial Q_i/\partial M > 0$), this second term should be positive as in the standard income effect.

The last term on the right hand side in the Slutsky with respect to wage (equation 14) is an additional term that represents a reevaluation of the time endowment. It is derived from the wage rate's influence on full income M. This can be thought of as the “time-income effect.” Since T will always be positive and $\partial Q_i/\partial M > 0$, the time-income effect will be positive as well.

We are able to predict the expected signs for all right-hand-side terms in both Slutsky equations. In the standard Slutsky (equation 13), we are also able to predict that the left-hand-side uncompensated change will be negative when $i = k$ or when i and k are complements. It could be either positive or negative when i and k are substitutes depending on the relative magnitudes of the substitution and income effects. For the modified Slutsky (equation 14), the addition of the time-income effect means that we are not able to predict the sign of the left-hand-side uncompensated change in any cases since it will depend on the relative magnitudes of all three right-hand-side terms.

Fig. 7 is adapted from Deaton and Muellbauer (1980b) and compares the income and substitution effects of a price increase with a wage increase. An increase in a typical price (panel a) rotates the budget line inward (CA to CA') whereas an increase in the wage (panel b) rotates the budget line upward (CA to C'A). Panel (a) shows that the effect of a price increase is negative for both goods and leisure since all else equal, a price increase makes the consumer less well off (B to B'). Panel (b) shows that the effect of a wage increase is quite different since there is a time-income effect in addition to the same substitution and income effects. The wage increase makes leisure relatively more expensive than the good, but it also increases full-income meaning the consumer can potentially buy more of any good. The wage increase illustrated has a negative effect on the amount of leisure consumed and a positive effect on the amount of the good consumed (B to B"). The difference between CA' and C'A which is visible in panel b is the result of the reevaluation of time allocation.

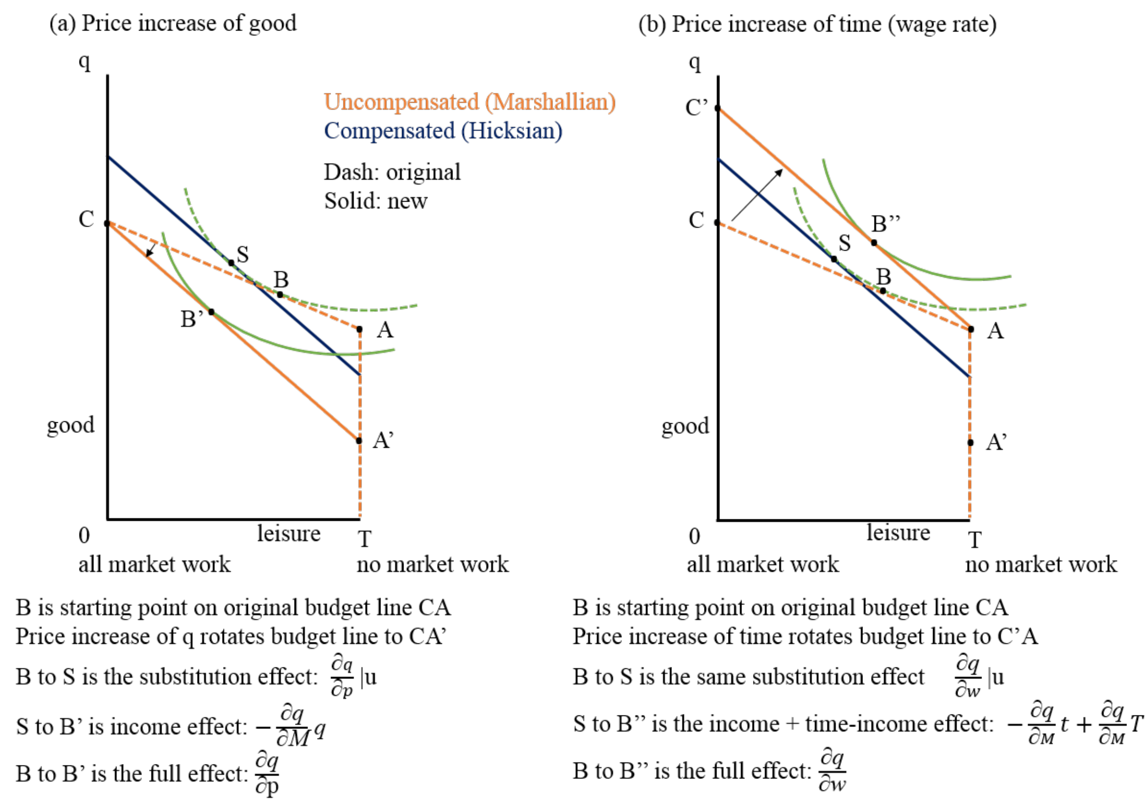

Figure 7: Decomposition of income and substitution effects for a price increase (panel a) and a wage increase (panel b).

We can use the two Slutsky equations to derive the relevant elasticities.[7] The "full-income elasticity of demand" is analogous to the standard income elasticity of demand. It is expected to be positive since all goods and leisure are expected to be normal. Equation 15 represents the full-income elasticity for any good or leisure, Q_i.

$$\varepsilon_{Q_i}^{M} = \underbrace{\frac{\partial Q_i}{\partial M} \cdot \frac{M}{Q_i}}_{(+)} \tag{15}$$

Uncompensated elasticities of demand with respect to prices of any good k, are

[7]See Equation 29 in the Appendix for derivations.

obtained from the standard Slutsky (equation 13):

$$\varepsilon_{ik} \;\; = \;\; \varepsilon_{ik}^{c} - \left(s_k \cdot \varepsilon_{Q_i}^{M}\right) \tag{16}$$

Uncompensated elasticities of demand with respect to the price of leisure are obtained from the modified Slutsky equation (14):

$$\varepsilon_{it_l} = \varepsilon_{it_l}^{c} - \left(s_{t_l} \cdot \varepsilon_{Q_i}^{M}\right) + \varepsilon_{Q_i}^{M} \tag{17}$$

9.3 Hypotheses

I developed two testable hypotheses for the full-income demand system with goods and leisure where food is divided into groups based on the associated preparation time. The first hypothesis is based on the existing literature which has found that consumers shift towards more convenient food options as the opportunity cost of time increases. Full-income elasticities for food at home are expected to be in the normal good range $(0, 1)$ with full-income elasticity for foods that require more preparation time (HP) smaller in magnitude than for foods that require little or no preparation time. Both at-home food groups are also expected to be less full-income elastic than food away from home $\left(\varepsilon_{q_{HP}}^{M} < \varepsilon_{q_{LP}}^{M} < \varepsilon_{q_{FAFH}}^{M}\right)$.

The second hypothesis follows from the model. Since both unpaid household production and leisure have the same price, they occur additively in the modified Slutsky (equation 14). High preparation foods require more household production than low preparation foods so $t_{h,HP} > t_{h,LP}$. All else constant, that implies high preparation foods effectively have a lower maximum potential amount of leisure available to a consumer $(T - t_h)$ compared with lower preparation foods (T).

Fig. 8 is a graphical illustration of the Marshallian uncompensated effect of an increase in the price of time for low preparation foods (left) compared with high preparation foods (right). The low preparation foods have a greater maximum potential amount of leisure. For the same wage rage increase θ, the demand for low preparation foods is more responsive than that of the high preparation foods. Thus, I expect that the uncompensated elasticity of demand for high preparation food with respect to the wage rate will be less than that for low preparation food $(|\varepsilon_{HP,t_l}| < |\varepsilon_{LP,t_l}|)$. Since food away from home contains both fast food and time intensive full service dining, I do not extend the hypothesis to that group.

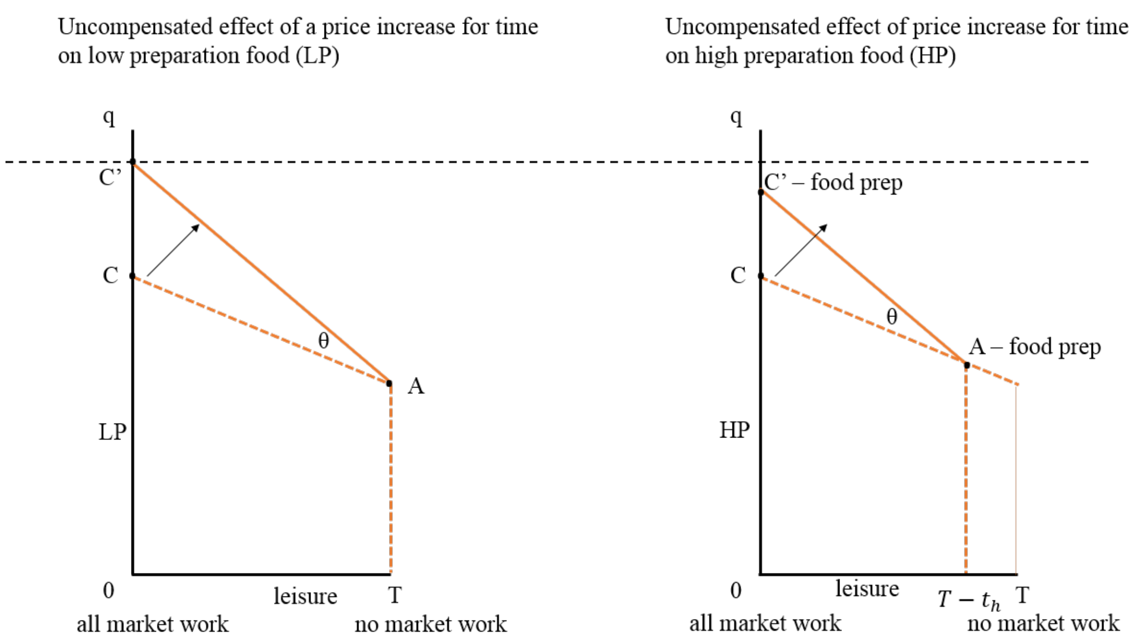

Figure 8: Decomposition of wage increase on low and high preparation foods.

10 Data overview

To test the hypotheses related to foods with different preparation times, I used a few nontraditional approaches to demand system estimation. To include data for leisure in the demand system, I used nationally-representative time-use averages from the American Time Use Survey. The time averages are calculated for different demographic cohorts and matched via cohort to Nielsen Homescan consumer households. The matching allowed me to do a cross-sectional cohort analysis of demand elasticities for the different demographic groups in addition to exploring the hypotheses. I also categorized the food products in the Nielsen data by the amount of associated preparation time in order to create the aggregate groups for high preparation foods and low preparation foods. The budget tree for the Part II demand system is pictured in Fig. 9.

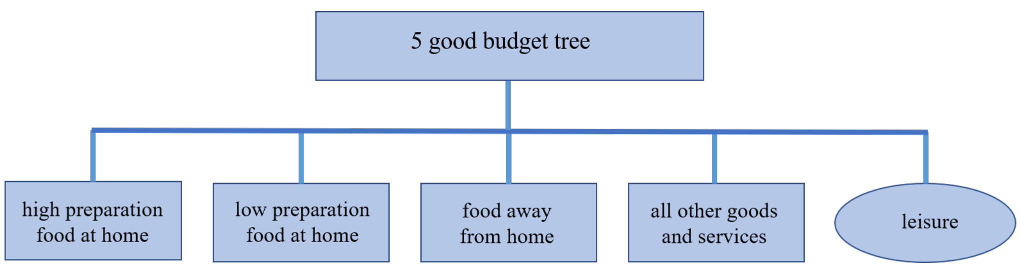

Figure 9: Budget tree for complete demand system including leisure.

Prices, quantities, and expenditures for the two food at home categories are from Nielsen's 2016 U.S. national Homescan consumer panel, as well as demographic data and money expenditures used in the analysis. Nielsen aims to capture purchases of consumer goods used in the home from a wide variety of retail outlets. The survey is implemented at the household level, and household respondents may participate for up to 27 months. Households scan all of their purchases using a home scanning unit provided by Nielsen. The purchase data are at the product level with accompanying descriptions which allowed me to group products by preparation time. The unit of observation is the panelist's average weekly purchases in each month. If a panelist participated with Nielsen for the whole year, I have 12 (monthly) observations corresponding to that panelist. The weekly averaging of a month's worth of purchases helps overcome the potential problem of zero-purchase censoring that is common in demand analysis. Remaining zeros in the data are assumed to be actual non-purchases since they mean a panelist consistently did not buy that category of food during the whole month.

Time use quantities and prices of time are from the Bureau of Labor Statistics (BLS) American Time Use Survey. Participants are drawn from the sample of people who have successfully completed the BLS Current Population Survey. The survey samples one individual in a household who reports their time use for a 24 hour period in a time diary format. Weighted average daily hours of market work, household non-market work, and leisure activities are calculated based on the ATUS 2003-2015 data file.[8] Time use patterns have changed little over this period, and ATUS provides nationally representative weights specifically for the data set covering that entire period.

Average weekly expenditures on food away from home and all other goods and services are calculated for each demographic cohort from the Consumer Expenditure Survey (CEX). Prices for food away from home come from this survey as well. The regional monthly BLS CPI for all items less food is used as a price index for all other goods.

[8]See Appendix Table 24 for time use codes in each category

10.1 Food classification system

The food classification systems comprise three general approaches: time-saving, degree-of-processing, and degree-of-readiness (Harris and Shiptsova, 2007). Many of these classification systems use “convenience,” although each tends to define that term in a slightly different way. An even greater number of studies examine demand for “convenience foods,” especially food away from home, but again, a universal metric of convenience does not appear to exist across the literature. Furthermore, as food preparation practices have shifted over time, some of the older notions of convenience are less relevant for analyzing demand today. Store-bought pickles are certainly a time-saving product compared to making pickles at home, but most current U.S. households would never consider the latter option. Alternatively, simply eating raw cucumbers could also be considered time-saving compared to making pickles, and these classification systems can break down.

Another aspect of many time-based food classification systems, especially those that take a degree-of-processing approach, is a distinction between basic ingredients, complex ingredients, and “meals and snacks” ((Capps Jr. et al., 1985; Richardson et al., 1985; Okrent and Kumcu, 2016)). From the food manufacturer’s view point, an ordinal trend of value added by processing is clear in these groupings. From the consumer’s view point, though, this categorization does not necessarily imply increasing convenience. Milk and apples are highly convenient snacks but would be considered basic ingredients along with dried beans which take a long time to prepare.

To accurately represent the consumer’s perspective regarding preparation time, I follow a degree-of-readiness approach using a scale of 14 categories developed and tested by Pearson et al. (1985). The detailed categories are based upon the degree and type of preparation households must contribute to foods before eating. The categories range from “eat as is” to the “eviscerate, prepare for cooking, then cook.” Pearson et al. (1985) also defines a heuristic for aggregating these 14 categories into three groupings to simplify analysis: “no preparation,” “some preparation,” and “considerable preparation.” I used a slightly modified and renamed round of these three groupings to better reflect current cooking habits: “no preparation,” “low preparation,” and “high preparation.”

Table 9 displays the 14 categories from Pearson et al. (1985) with descriptions, and aggregate groupings, as well as my aggregate groupings. The only actual difference between the groupings is a conceptual change of where the dividing line falls between the middle and highest preparation groupings. Two categories (“Thaw then cook” and “Hydrate then cook”) are shifted from the middle to the highest preparation grouping because the preparation time required it the main focus here. Even with that change, Table 10 shows that only 3 percent of food products in Nielsen’s product dictionary fall into the “high preparation” category which reflects the food manufacturing industry’s introduction of many time-saving products. Table 10 displays the number and percent of products in the Nielsen dictionary and purchased by consumers in the sample broken down by the categories used in Part II: “high preparation” and “low preparation” which also include “no preparation”.

One other common feature in the literature on time-based food classification systems is use of the terms or categories “ready to eat” and “ready to cook.” As with the term “convenience,” these frequently take on different meanings in different studies. All three terms are also commonly used in the vernacular, increasing potential confusion, and I will generally avoid them in this paper.

Table 9: Food categories used in (Pearson et al., 1985) (I), Part II, and Part III.

<table>
<tr><th></th><th>Category Name</th><th>Category Description</th><th>I</th><th>II</th><th>III</th></tr>
<tr><td>00</td><td>Eat as is</td><td>Products requiring no further processing to achieve a servable form. Includes only products which are consumed as purchased.</td><td rowspan="2">No prep.</td><td rowspan="9">Low preparation</td><td rowspan="2">No prep.</td></tr>
<tr><td>01</td><td>Ready to use</td><td>Products that are servable but which are typically used in combination with other foods rather than served alone. Also includes ingredient foods which have convenience attributes.</td></tr>
<tr><td>02</td><td>Cut slice, shell</td><td>Foods which are eaten raw but have to be trimmed, cut, sliced or shelled first. Includes ready-to-eat and ready-to-use items that require cutting, peeling or slicing.</td><td rowspan="9">Some preparation</td><td rowspan="7">Low preparation</td></tr>
<tr><td>03</td><td>Thaw</td><td>Foods which have been frozen from the ‘eat-as-is’ form and only require thawing prior to consumption. Also includes items frozen from ‘ready-to-use’ form.</td></tr>
<tr><td>04</td><td>Hydrate</td><td>Foods which require addition of a liquid, most frequently water, prior to consumption. Includes several items where one ingredient such as sugar is also added.</td></tr>
<tr><td>05</td><td>Ready to heat</td><td>Products which need only heating to obtain servable form. Usually includes fully cooked foods which are not consumed cold.</td></tr>
<tr><td>06</td><td>Thaw then heat</td><td>Foods that have been frozen in ‘ready-to-heat’ form and only require thawing prior to heating. Includes fully cooked foods which are not consumed cold.</td></tr>
<tr><td>07</td><td>Hydrate then heat</td><td>Foods which require addition of a liquid, most frequently water, prior to heating. Also includes foods hydrated with heated water.</td></tr>
<tr><td>08</td><td>Ready to cook</td><td>Foods in a readiness state allowing direct cooking to achieve a servable form. Also includes commercially frozen breaded products and nuts which must be roasted or boiled.</td></tr>
<tr><td>09</td><td>Thaw then cook</td><td>Foods which have been frozen in ‘ready-to-cook’ form and only require thawing prior to cooking.</td><td rowspan="5">High preparation</td><td rowspan="5">High preparation</td></tr>
<tr><td>10</td><td>Hydrate then cook</td><td>Foods which require the addition of a liquid, most frequently water, prior to cooking.</td></tr>
<tr><td>11</td><td>Cut, peel, or shape, then cook</td><td>Items which must be pared, peeled, shelled, trimmed, cut, scaled, shaped or skinned before cooking. Also foods which must be thawed before cutting, scaling or shaping before cooking.</td><td rowspan="3">Considerable prep.</td></tr>
<tr><td>12</td><td>Add other foods, then cook</td><td>Foods which require other ingredients as well as manipulation prior to cooking. Also frozen items which must be thawed prior to the addition of other ingredients and subsequent cooking.</td></tr>
<tr><td>13</td><td>Eviscerate, prepare, cook</td><td>Items which must be eviscerated prior to preparation for cooking. Includes frozen live-weight meat, fish and poultry which first must be thawed, then prepared for cooking.</td></tr>
</table>

Table 10: Products in Nielsen 2016 by preparation category.

	Product dictionary	Consumer purchases
High preparation	41,137 (3%)	617,036 (7%)
Low preparation	1,368,355 (97%)	8,721,031 (93%)

10.2 Demographic cohorts

Following matching methods in Aguiar and Hurst (2007) and Hamermesh (2007), I used demographic cell matching to combine Nielsen data with the ATUS and CEX. Four characteristics were used to create 128 demographic cohorts. The characteristics were age (Under 35 Years, 35-49 Years, 50-64 Years, 65+ Years), gender, race/ethnicity (non-Hispanic White, non-Hispanic Black, non-Hispanic Asian/other, and Hispanic), and categories based on income relative to the federal poverty line controlling for household size. The income categories include: very-low income ($\leq$ 130 percent of the poverty line), low income ($\leq$ 250 percent of the poverty line), mid income ($\leq$ 500 percent of the poverty line), and high income ($<$ 500 percent of the poverty line). The sample is comprised of working, single-headed households in order to estimate the most parsimonious version of the simple labor supply model to explore the hypotheses. Table 11 lists the demographic breakdown of Nielsen panelists.

10.3 Expenditure shares on goods and leisure

Expenditures for high preparation and low preparation foods were calculated as actual weekly averages for each panelist in each month. Nationally representative

Table 11: Demographic breakdown of Nielsen panelists.

Age		Household size	
Under 35 years	962	1	6226
35-49 years	2,860	2	2193
50-64 years	4,920	3	934
65+ years	1,265	4+	654
Income category		Race/ethnicity	
Very low income	798	White	7,338
Low income	2,200	Black	1,631
Mid income	4,027	Asian/other	538
High income	2,982	Hispanic	500
Gender		Region	
Male	2,665	Northeast	1,905
Female	7,342	Midwest	2,512
		South	3,669
Kids		West	1,921
No kids	8,587		
Kids	1,420	Total	10,007

weighted-average weekly expenditures for all other goods and services and for food away from home were calculated by cohort using the CEX. For leisure, I calculated nationally-representative weighted averages using the ATUS activity codes for socializing, relaxing, leisure, sports, exercise, recreation, volunteering, fun activities with household children, fun activities with non household kids, and related travel. Descriptive statistics for shares are listed in Table 12 including mean, standard deviation, minimum, maximum and percentage of zeros.

Table 12: Descriptive statistics of expenditure shares, prices, and full income

Variable	Mean	SD	Min	Max	Zeros
Share of high preparation food	0.00	0.01	0.00	0.11	19%
Share of low preparation food	0.04	0.03	0.00	0.44	0%
Share of food away from home	0.03	0.02	0.00	0.17	0%
Share of all other goods & service	0.38	0.10	0.00	0.73	0%
Share of leisure time	0.55	0.10	0.14	0.99	0%
Price of high preparation food ($/product)	2.82	0.53	0.01	23.73	
Price of low preparation food ($/product)	2.12	0.23	0.15	14.99	
Price of food away from home ($/occasion)	7.72	1.57	1.94	18.81	
Price of all other goods & service (CPI)	0.94	0.05	0.87	1.02	
Price of leisure (wage rate)	25.54	13.10	3.13	130.21	
Full income	2257.69	1094.52	84.04	12372.02	

10.4 Prices for goods and leisure

Descriptive statistics for prices in the full sample are reported in the bottom panel of Table 12. Prices for the three food groups were calculated as regional-monthly geometric means of the disaggregate product prices for each income category to control for quality and ensure cross-sectional price variation (Cox and Wohlgenant, 1986). Mean prices by income category and by region are displayed in Table 13. The prices derived from Nielsen data (high preparation and low preparation) are at the county-level and the food away from home price is at the Census regional-level (northeast, midwest, south, west). I used the monthly-regional Consumer Price Index for all items less food as the price index for all other goods and services. Non-purchases for all groups were assigned the relevant monthly-regional prices for the corresponding income category (Cox and Wohlgenant, 1986).

Table 13: Mean prices by income category and region

Variable	Very low income	Low income	Mid income	High income
Mean price of high preparation food	2.78	2.72	2.76	2.99
Mean price of low preparation food	1.97	1.99	2.09	2.29
Mean price of food away from home	7.46	7.47	7.67	8.06
Mean price of all other goods & service	0.94	0.94	0.94	0.95
Mean price of leisure (wage rate)	7.05	14.00	23.07	42.30
	Northeast	Midwest	South	West
Mean price of high preparation food	2.90	2.77	2.80	2.84
Mean price of low preparation food	2.18	2.08	2.10	2.15
Mean price of food away from home	7.81	7.42	7.48	8.51
Mean price of all other goods & service	1.01	0.89	0.91	0.98
Mean price of leisure (wage rate)	27.08	23.91	25.46	26.28

ATUS reports annual income of participants in 16 categories. I used the midpoint of each category to create a weekly income approximation for each participant. For each demographic cohort, weighted average weekly income (m^{ATUS}) was calculated and divided by the weighted average weekly working hours (t_w) to generate a weighted average wage rate (w^{ATUS}) to use as the price of leisure.

$$w^{ATUS} = \frac{m^{ATUS}}{t_w} \tag{18}$$

I also created two other versions of proxy wage rates as potential candidates for the price of leisure. The second uses Nielsen data exclusively and is used in Part III. The Nielsen data contain a categorical variable for work hours (less than 30 hours, 30-34 hours, 35+ hours). I assigned a value to each category (20 hours, 32 hours, 40 hours) and used that value to divide reported weekly income for each panelist. The third wage rate is a hybrid using Nielsen income divided by working hours from the corresponding ATUS cohort. Table 14 lists the range, quartiles, mean, and standard deviation for the three wage rate proxies which have comparable distribution.

Table 14: Wage rate proxies from ATUS, Nielsen, and hybrid

	Min	25th percentile	50th percentile	75th percentile	Max	Mean	SD
ATUS	3.13	14.59	21.55	37.49	130.21	25.54	13.10
Nielsen	1.20	16.85	26.45	40.88	96.15	28.73	15.51
Hybrid	0.85	16.02	23.52	35.93	144.04	25.72	12.53

10.5 Full income

Full income M, is defined as the potential income that could be attained if all available hours T, were used in market work. Full income was calculated though a series of steps. First, the available hours for market work, home production, and leisure (T) were calculated from the ATUS data. Market work is defined as working or travel related to working. Home production includes food and drink preparation, presentation, clean-up, grocery shopping, non-food related household activities, caretaking, and travel related to any of those activities. Leisure includes socializing, relaxing, leisure, sports, exercise, recreation, volunteering, fun activities with household children, fun activities with non household kids, and related travel.

Next, the hybrid wage rate (Nielsen income divided by ATUS working hours) was multiplied by total available hours T to obtain a variable representing full income as shown in Equation 19. The hybrid wage rate was tested to be the best option for generating full income since use of the ATUS wage rate causes simultaneity problems and the Nielsen wage rate had limited information on working hours.

$$M = \frac{m^{NIEL}}{t_w} T \tag{19}$$

11 Estimation

To estimate the demand system, I used the Quadratic Almost Ideal Demand System (QUAIDS) model first introduced by Banks et al. (1997). It is a generalization of the Deaton and Muellbauer (1980a) Almost Ideal Demand System (AIDS) model that includes the square of the logarithm of expenditure as an additional regressor in order to accommodate quadratic Engel curves if warranted. Treating leisure as a normal good, the QUAIDS indirect utility function adapts seamlessly using full-income M:

$$\ln V = \left\{ \left[\frac{\ln M - \ln a(\boldsymbol{p})}{b(\boldsymbol{p})} \right]^{-1} + \lambda(\boldsymbol{p}) \right\}^{-1} \tag{20}$$

$$\begin{aligned}
\ln a(\boldsymbol{p}) &= \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \ln p_i \ln p_j \\
b(\boldsymbol{p}) &= \prod_{i=1}^{n} p_i^{\beta_i} \\
\lambda(\boldsymbol{p}) &= \sum_{i=1}^{n} \lambda_i \ln p_i \quad \text{where } \sum_i \lambda_i = 0
\end{aligned}$$

From Equation 20, the expenditure share equations for each good can be derived by applying Roy's identity and some algebra:

$$s_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln \frac{M}{a(\boldsymbol{p})} + \frac{\lambda_i}{b(\boldsymbol{p})} \left\{ \ln \frac{M}{a(\boldsymbol{p})} \right\}^2 \tag{21}$$

for $i \in (q_{HP}, q_{LP}, q_{FAFH}, q_{AOGS}, t_l)$. Adding up, homogeneity, and Slutsky symmetry were imposed:

$$\sum_{i=1}^{k} \alpha_i = 1, \qquad \sum_{i=1}^{k} \beta_i = 0, \qquad \sum_{j=1}^{k} \gamma_{ij} = 0, \qquad \text{and } \gamma_{ij} = \gamma_{ji}.$$

However, as noted by García-Enríquez and Echevarría (2016), it is not feasible to either test or impose negative semi-definiteness of the Slutsky substitution matrix.[9]

Demographic scaling It is generally acknowledged that factors in addition to prices and expenditure can help explain consumer consumption decisions. Demographic scaling for gender, household size, region, age, race/ethnicity, and the presence of kids was incorporated into the standard QUAIDS model using the technique introduced by Ray (1983) and extended by Poi (2012).

Let $\boldsymbol{z}$ represent a vector of characteristics. Let $e^R(\boldsymbol{p}, u)$ denote the expenditure function of a reference household, and the function $m_0(\boldsymbol{p}, \boldsymbol{z}, u)$ scales the expenditure function $e(\cdot)$ to account for different household characteristics.

$$e(\boldsymbol{p}, \boldsymbol{z}, u) = m_0(\boldsymbol{p}, \boldsymbol{z}, u) \times e^R(\boldsymbol{p}, u) \tag{22}$$

[9] "At most, one could always check, for instance, the sign of the eigenvalues of the estimated Slutsky substitution term matrices for each individual in the sample and obtain, say, the proportion of negative semi-definite matrix cases, or check the sign of the eigenvalues of the Hicksian term matrix evaluated at some centered moment, usually the mean or the median" (Garcia-Enriquez and Echevarria, 2016, pg. 326).

The scaling function can be further decomposed:

$$m_0(\boldsymbol{p}, \boldsymbol{z}, u) = \overline{m}_0(\boldsymbol{z}) \times \phi(\boldsymbol{p}, \boldsymbol{z}, u) \tag{23}$$

with $\overline{m}_0(\boldsymbol{z})$ measuring the increase in a household's expenditures as a function of the demographics without controlling for changes in consumption patterns, and $\phi(\boldsymbol{p}, \boldsymbol{z}, u)$ controlling for changes in the relative prices of actual goods consumed.

Poi (2012) parameterizes

$$\overline{m}_0(\boldsymbol{z}) = 1 + \boldsymbol{\rho}'\boldsymbol{z} \tag{24}$$

and

$$\ln \phi(\boldsymbol{p}, \boldsymbol{z}, u) = \frac{\prod_{j=1}^{k} p_j^{\beta_j} (\prod_{j=1}^{k} p_j^{\boldsymbol{\eta}_j'\boldsymbol{z}} - 1)}{\frac{1}{u} - \sum_{j=1}^{k} \lambda_j \ln p_j} \tag{25}$$

with $\boldsymbol{\rho}$ and $\boldsymbol{\eta}$ as vectors of parameters to be estimated. The expenditure share equations can now take the form:

$$s_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + (\beta_i + \boldsymbol{\eta}_i'\boldsymbol{z}) \ln \frac{M}{a(\boldsymbol{p})(1 + \boldsymbol{\rho}'\boldsymbol{z})} + \frac{\lambda_i}{b(\boldsymbol{p})c(\boldsymbol{p}, \boldsymbol{z})} \left\{ \ln \frac{M}{a(\boldsymbol{p})(1 + \boldsymbol{\rho}'\boldsymbol{z})} \right\}^2 \tag{26}$$

with

$$c(\boldsymbol{p}, \boldsymbol{z}) = \prod_{j=1}^{k} p_j^{\boldsymbol{\eta}_j'\boldsymbol{z}}$$

Adding up also requires $\sum_{j=1}^{k} \eta_{rj} = 0$ for $r = 1, ..., s$.

QUAIDS elasticities Equation 27 shows the QUAIDS uncompensated price elasticity of i with respect to changes in the price of j with demographic scaling for full income M with demographic scaling.

$$\begin{aligned} \varepsilon_{ij} \quad = \quad & -\delta_{ij} + \frac{1}{s_i}\left\{\gamma_{ij} - \left[\beta_i + \boldsymbol{\eta}_i'\boldsymbol{z} + \frac{2\lambda_i}{b(\boldsymbol{p})c(\boldsymbol{p},\boldsymbol{z})}\ln\left(\frac{M}{a(\boldsymbol{p})(1+\boldsymbol{\rho}'\boldsymbol{z})}\right)\right] \times \right. \\ & \left. \left(\alpha_j + \sum_l \gamma_{jl}\ln p_l\right) - \frac{\left(\beta_j + \boldsymbol{\eta}_j'\boldsymbol{z}\right)\lambda_i}{b(\boldsymbol{p})c(\boldsymbol{p},\boldsymbol{z})}\left[\ln\left(\frac{M}{a(\boldsymbol{p})(1+\boldsymbol{\rho}'\boldsymbol{z})}\right)\right]^2\right\} \end{aligned} \tag{27}$$

Equation 28 is the QUAIDS full-income elasticity for good i with demographic scaling.

$$\varepsilon_i^M = 1 + \frac{1}{s_i}\left[\beta_i + \boldsymbol{\eta}_i'\boldsymbol{z} + \frac{2\lambda_i}{b(\boldsymbol{p})c(\boldsymbol{p},\boldsymbol{z})}\ln\left(\frac{M}{a(\boldsymbol{p})(1+\boldsymbol{\rho}'\boldsymbol{z})}\right)\right] \tag{28}$$

Implementation I estimated the 5-good complete demand system and elasticities in Stata version 14.1 using the QUAIDS package (version st0268_1) developed by Poi (2012). Given the data aggregation strategy, all zero-purchases were considered true non-purchases and included in the demand system estimation using the prices for the corresponding region-month-income category. The value for α_0 was chosen to be 50 which is roughly the minimum expenditure in the sample with unit prices. Several other values of α_0 were tested as robustness checks, and $\alpha_0 = 50$ produced the highest log likelihood. Standard errors for parameters were clusters at the household level. Standard errors for elasticities were calculated using the delta method at the sample means.

12 Results

Parameter results for the estimation are listed in Tables 25 and 26 in the Appendix. Full-income and uncompensated price elasticities of demand for the full sample demand system are reported in Table 15 with standard errors in parentheses. Overall, while there are slight differences between high and low preparation foods in full-income elasticity and cross-price elasticity with respect to leisure in the expected direction, the values for the two food groupings are in fact very close and statistically indistinguishable in this specification and several others.

Interpretation of the full-income elasticity remains the same as it would be for the more common income elasticity since everything else (including wage) is held constant and therefore no reevaluation of time takes place. One point to remember when comparing full-income elasticities with typical income elasticity estimates is that collectively the full-income elasticities sum to one with budget shares as weights. On average, leisure in the system represented more than half of expenditures ($s_{t_l} = 0.55$) as reported in Table 12. Given the large share of leisure expenditure, the full-income elasticities of other goods might differ from standard expectations as the system incorporates leisure. In fact, results in Table 15 did show full-income elasticities for both at-home food groups as slightly above one indicating those groups are just barely on the side of luxuries which is not typically expected. Leisure, however, was found to be a normal good, so the at-home full-income elasticities make sense in this system as a whole.

Food away from home and all other goods and services also had full-income elasticities above one which are consistent with expectations from previous studies. Park et al. (1996) found expenditure elasticity of food away from home and alcohol to be 1.42, but they did not look at other (nonfood) goods and services. Reed et al. (2005) found income elasticity of food away from home and alcohol to be 1.38 and that of nonfood to be 0.92. Okrent and Alston (2012) found the expenditure elasticity of food away from home and alcohol to be 0.21 which seems low, but is still their second highest expenditure elasticity after nonfood which they found to be 1.21.

The hypothesized relationship that full-income elasticity of high preparation food ($\varepsilon^M_{q_{HP}} = 1.015$) is less elastic than for low preparation food ($\varepsilon^M_{q_{LP}} = 1.018$) had weak and insignificant support. The full-income elasticity of food away from home was more elastic than either of the at-home food groups ($\varepsilon^M_{q_{FAFH}} = 1.071$), but we cannot rule out the possibility of the null hypothesis at reasonable confidence levels. Additionally, robustness checks indicate that the full-income elasticities are susceptible to change with different specified values of α_0. In all robustness specifications, full-income elasticity for food away from home was found to be more elastic than both at-home food groupings, but the relationship between high and low preparation foods did not hold consistently.

Table 15: Full-income and uncompensated price elasticities, 5-good system.

Elasticity of demand for:	with respect to price of:					
	Full-income	HP	LP	FAFH	AOGS	Leisure
High preparation foods (HP)	1.015 (0.046)	-0.390 (0.041)	-0.184 (0.093)	0.049 (0.029)	0.228 (0.091)	-0.720 (0.054)
Low preparation foods (LP)	1.018 (0.025)	-0.020 (0.010)	-0.604 (0.053)	0.068 (0.017)	0.283 (0.051)	-0.745 (0.030)
Food away from home (FAFH)	1.071 (0.015)	0.006 (0.004)	0.075 (0.019)	-0.977 (0.006)	0.182 (0.020)	-0.356 (0.017)
All other goods & services (AOGS)	1.058 (0.009)	0.002 (0.001)	0.028 (0.006)	0.017 (0.002)	-0.926 (0.008)	-0.180 (0.010)
Leisure time (Leisure)	0.954 (0.006)	-0.005 (0.000)	-0.051 (0.001)	-0.019 (0.001)	-0.085 (0.004)	-0.794 (0.007)

Notes: Estimates of elasticities of demand were computed at the mean of the data. Standard errors are in parentheses.

Table 15 also shows weak and statistically insignificant support for the second hypothesis that high preparation foods will be less responsive to the price of leisure than low preparation foods ($|-0.720| < |-0.745|$). These elasticities with respect to the price of leisure can be thought of as shadow prices since full-income (and therefore the actual wage) is fixed. In a dual-headed household model, a change in the shadow price of a homemaker would occur if the working partner received a wage increase. In this single-headed model, a change in the shadow price of time could be thought of as occurring if the household got a pet or started caring for a sick relative.

All own-price elasticities of demand are negative as expected. The own-price elasticity for high preparation foods (-0.390) is substantially less elastic than that for low preparation foods (-0.604) suggesting that the demand for high preparation foods as a group is less responsive to its own price than that for low preparation foods as well. The price elasticities were robust across the alternate specifications of α_0 and other robustness checks.

The same price elasticities for the full sample are illustrated as a heat map in Fig. 10. White blocks indicate inelasticity (ε_{ij} near zero); with increasingly darker shades indicating greater elasticity. In Fig. 10, positive and negative signs are overlaid on each block (or 0 if the elasticity is not significantly different than zero). The own-price elasticity for food away from home stands out as the darkest shade (most elastic) with elasticity just under -1. The relatively dark diagonal of negative own-price elasticities is distinct. Positive cross-price elasticities indicate substitutes whereas negative cross-price elasticities indicates complements.

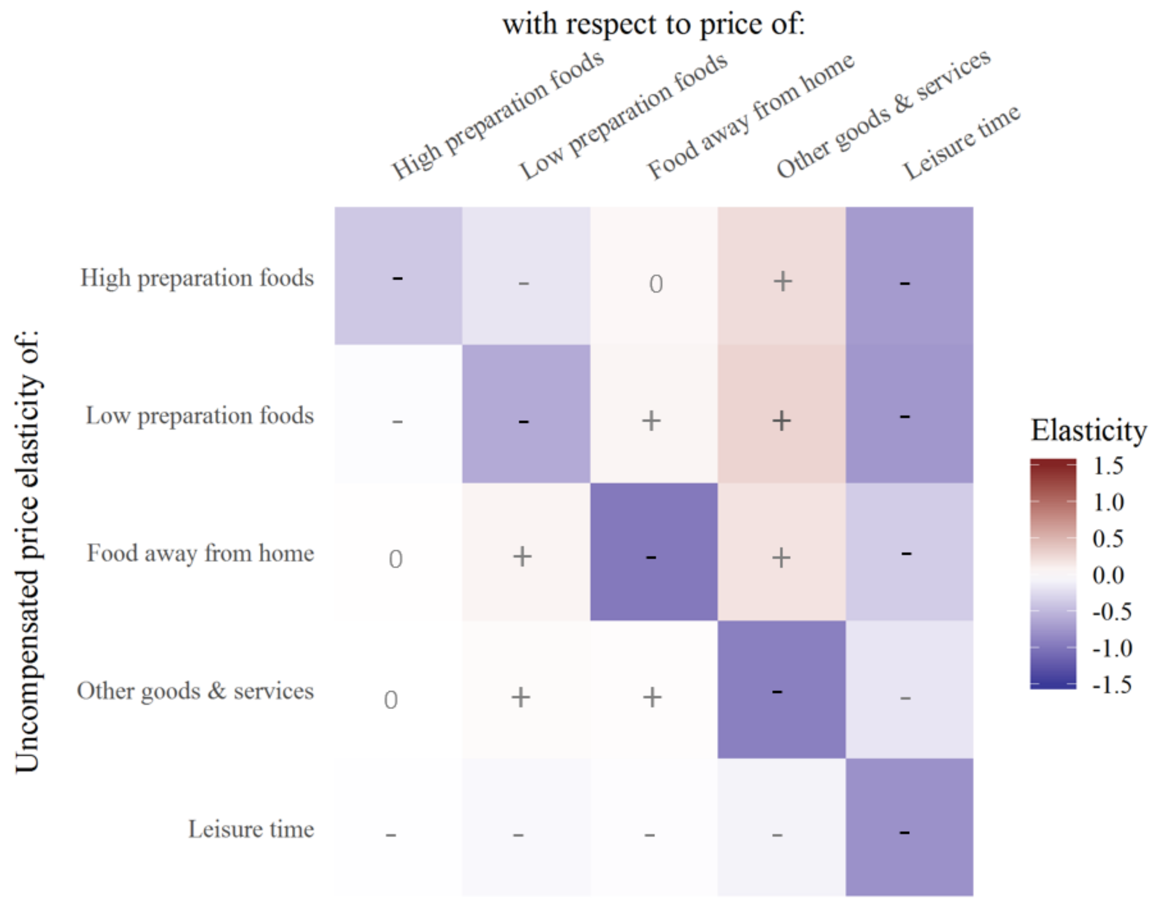

Figure 10: Price elasticity heat map, full sample (n = 59,307).

Figs. 11 through 14 are heat maps comparing price elasticities between genders, income categories, household size, and race/ethnicity. The heat map visualization of elasticity data allows for quick comparisons of a large number of elasticities across demographics. The signs of elasticity (+/-) remain the same in Figs. 11 through 14 as in 10 so they were not included, with an exception indicated on Fig. 12.

Figure 11: Price elasticity heat map, by gender: male (left, n = 15,881), female (right, n = 43,426).

Fig. 11 presents price elasticities for male panelists on the left and female on the right with few discernible differences. Fig. 12, however, shows clear patterns as income level increases from very low income on the far left to high income on the far right. The own-price elasticity for high preparation foods (upper left block) becomes less elastic as income category increases and is completely inelastic[10] in the highest income category. High preparation foods show the reverse trend and become more elastic in response to the price of low preparation foods as income category increases. Demand for both at-home food groups become much more responsive to the shadow price of leisure as income category increases (upper two blocks of the far right column).

[10]statistically indistinguishable from zero (0.047)

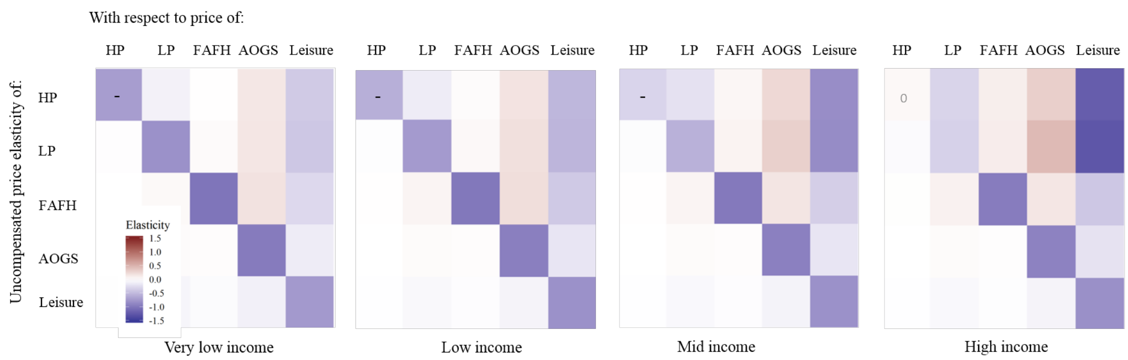

Figure 12: Price elasticity heat map, by income category: very low (far left, n = 4,660), low (center left, n = 13,025), mid (center right, n = 23,849), high (far right, n = 17,773).

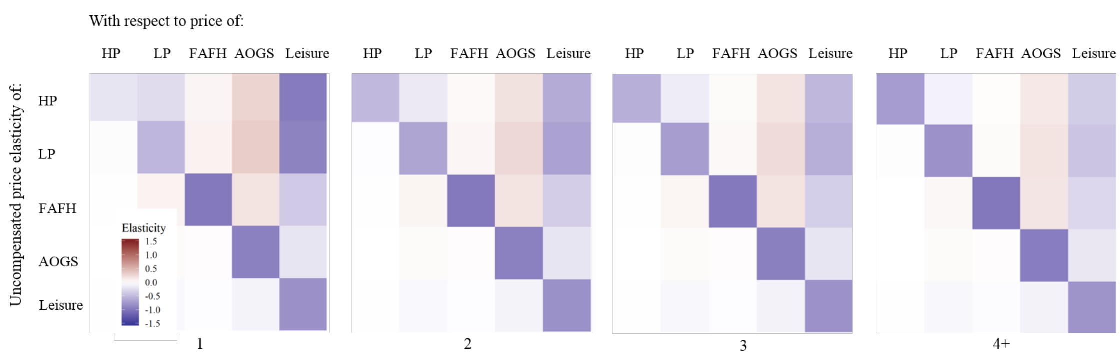

Figure 13: Price elasticity heat map, by household size: 1 (far left, n = 36,724), 2 (center left, n = 13,218), 3 (center right, n = 5,475), 4+ (far right, n = 3,890).

Fig. 13 presents the set of price elasticity heat maps for increasing household size which shows the reverse of the trends in the income maps. Fig. 14 is the set of price elasticity heat maps by race/ethnicity which show very little variation across groups.

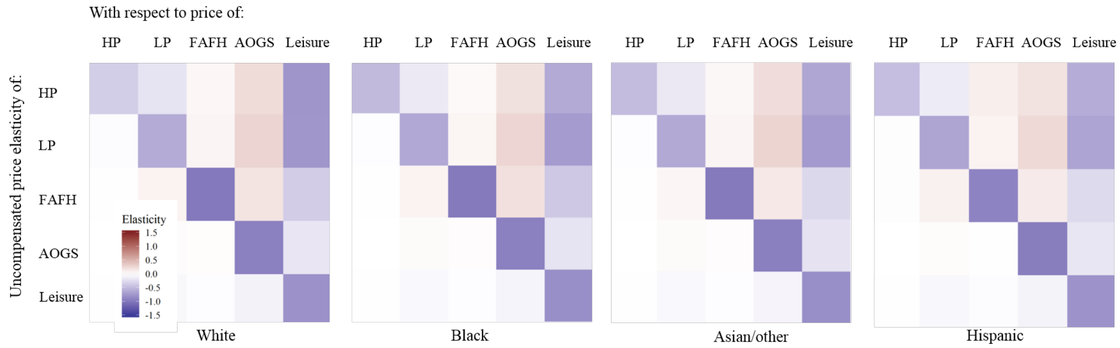

Figure 14: Price elasticity heat map, by race/ethnicity: White (far left, n = 43,598), Black (center left, n = 9,587), Asian/other (center right, n = 3,233), Hispanic (far right, n = 2,889).

13 Discussion

While there were differences in own-price elasticities between high and low preparation foods, these could not be predicted within the theoretical framework and might be due to product characteristics unrelated to time. Results showed weak but insignificant support for both hypotheses. The full-income elasticities for high and low preparation foods were very close as were the cross-price elasticities of each of those groups with respect to the shadow price of leisure. These null results suggest that it might not be necessary to divide at-home foods by preparation time when incorporating leisure time as a good in the demand system. If so, this increases the food expenditure data options that could be used in future analysis and also raises the question of whether the opportunity cost of time is already factored into the prices of at-home foods.

If time cost is already factored into the prices, then it follows that change in demand would be similarly responsive to the price of time for both high and low preparation groups at this aggregate level. Some support for this idea can be found in the literature. In a hedonic analysis of breakfast sausage, Vickner (2015) found a 45 cent per pound premium for the "cooked" attribute while controlling for other important product characteristics. Future work could focus at the product level to better control for other product characteristics and hone in on time-saving attributes.

Synthesis of the elasticity results across different demographic cohorts collectively indicates that economic factors (income and household size) played a greater role in demand responsiveness for food than social characteristics (gender, race/ethnicity). Other studies have found gender-based differences, but since this sample focuses on single-headed working households in 2016, it is not surprising that demand responses were similar across genders.

All else equal, increasing income category and increasing household size showed opposite trends with low (high) income and large (small) household size displaying similar patterns. This mirroring can be thought of in terms of discretionary income with high incomes or small household sizes indicating greater discretionary income. Increasing discretionary income corresponds to less elastic own-price demand for high and low preparation foods and more elastic cross-price demand with respect to the shadow price of leisure. As consumers gain higher discretionary income, they become less responsive to the price of at-home food and more responsive to the shadow price of time.

The differences in demand responsiveness across incomes have implications for healthy eating strategies. Consumers with lower incomes are more responsive to changes in food prices than to changes in the shadow price of time whereas the reverse is true at higher income. Discounts, subsidies, and other price-based incentives for healthy food consumption might work better for low income consumers than for high income consumers. Increased availability of time-saving healthy food options might be a better approach for targeting high income consumers. Of course, any healthy eating promotion must compete within a vast landscape of unhealthy options, and the results presented here do not provide guidance on consumer propensity to substitute among healthy and unhealthy options though that could also be pursued in future work.

Part III

Demand system incorporating the cost of time

14 Extension of Theory

Given the lack of available data for consumers with both disaggregated expenditures and time use, it is worth exploring other ways of incorporating the value of time into a demand system. For future empirical extensions related to policy questions, it would be advantageous to develop a model that does not need to rely on demographic matching of separate data sets. Additionally, parameter estimates and elasticities should be evaluated based on their ability to predict consumer responses.

Revisiting the work by Mincer (1963), the properly defined price that a consumer faces is not the market price p, but rather $P = p + c$ where c is the opportunity cost of time. Foods with different associated preparation times might have different levels of opportunity cost where the time cost associated with high preparation foods is the highest and is zero for no preparation foods ($c_{HP} > c_{LP} > c_{NP} = 0$). Additionally, even if prices do not vary in cross-section, opportunity costs would vary again by individual if they are derived from wage rates. Thus, even if prices are fixed in cross section, opportunity costs are not. If the opportunity costs are a function of the wage rate, their omission will bias the parameter estimates.

In regards to food purchases, the opportunity cost of time to prepare food can be significant. Davis and You (2010) found that the time cost share of total food cost can range from 30-49 percent. Neglecting the opportunity cost of food preparation in demand system estimates of food elasticities could be leading to biased parameter estimates. The work presented which follows is a new exploration of integrating the opportunity cost of time into a demand system without having to incorporate leisure as an additional good. Two new potential methods are described and tested with results reported and compared.

15 Methods

A conventional food demand system with eight goods is used for this analysis including groups of (1) *cereals and bakery*; (2) *produce*; (3) *meat, eggs, seafood*; (4) *dairy*; (5) *nonalcoholic beverages*; (6) *other food*; (7) *food away from home*; (8) *all other goods and services.* This categorization is based on Okrent and Alston (2012) with the only difference being that alcohol is included in all other goods and services here rather than with food away from home. Fig. 15 illustrates the budget tree. This 8-good demand system also allows for easier comparison with existing literature (Park et al., 1996; Reed et al., 2005; Okrent and Alston, 2011).

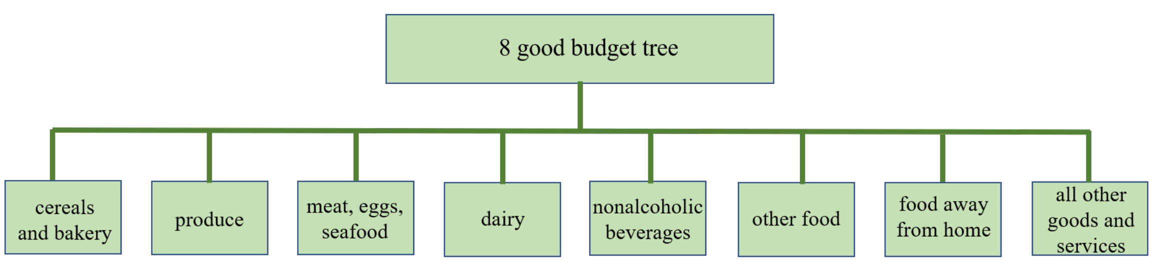

Figure 15: Budget tree with 8 goods.

Within each group, it is assumed that different products still have different associated preparation times. Table 16 is a cross-tabulation of the at-home food groups with preparation time categories from the Part III section of Table 9 (high preparation, low preparation, and no preparation).

Three specifications of this demand system were tested. The first specification uses standard prices calculated the same way as in Part II (regional-monthly geometric means by income category). This specification serves as a baseline for comparison with the two new methods and existing literature. The second specification scales up prices by 65 percent for high preparation foods and 15 percent for low preparation foods. These figures in particular were chosen since they scale up total costs to account for a 30 percent preparation time cost based on lower bound of results in Davis and You (2010). However, these percentage markups do not vary across consumers.

Table 16: Products in 2016 Nielsen data by preparation time and food category.

	High preparation		Low preparation		No preparation		Total
Cereals and bakery	16,193	(1%)	46,909	(3%)	266,672	(19%)	329,774
Produce	7,039	(0%)	64,677	(5%)	79,000	(6%)	150,716
Meat, eggs, seafood	6,061	(0%)	46,906	(3%)	31,103	(2%)	84,070
Dairy	0	(0%)	1,377	(0%)	129,656	(9%)	131,033
Nonalcoholic beverages	0	(0%)	48,501	(3%)	102,117	(7%)	150,618
Other food	11,844	(1%)	108,517	(8%)	442,920	(31%)	563,281

The third specification added a percentage of an individual's wage rate as a cost. These additional costs do vary by consumer. The wage rate used is the Nielsen-derived rate summarized in Table 14, since it can be created from within the Nielsen data alone. For high preparation foods, 75 percent of an hour's wage rate is added and 25 percent is added for low preparation foods. Prices and expenditures for all three specifications are aggregated in the same manner as in Part II. The three 8-good specifications were all estimated using QUAIDS with demographic scaling in the the same way as the 5-good specification in Part II, but with $\alpha_0 = 3$ as the minimum system expenditure using unit prices and the use of the standard money income (m) rather than full-income (M).

Table 17: Mean expenditure shares and prices for 8-good specifications.

	Standard	Scaled	Added time cost
Mean share of cereals and bakery	0.014	0.014	0.021
Mean share of produce	0.013	0.015	0.030
Mean share of meat, eggs, seafood	0.015	0.020	0.031
Mean share of dairy	0.011	0.011	0.010
Mean share of nonalcoholic beverages	0.011	0.012	0.013
Mean share of other food	0.034	0.034	0.044
Mean share of food away from home	0.079	0.079	0.074
Mean share of all other goods & services	0.823	0.815	0.776
Mean price of cereals and bakery	2.07	2.19	3.09
Mean price of produce	1.72	1.93	4.21
Mean price of meat, eggs, seafood	3.73	4.69	9.29
Mean price of dairy	2.23	2.23	2.23
Mean price of nonalcoholic beverages	2.04	2.11	2.61
Mean price of other food	2.23	2.34	3.37
Mean price of food away from home	7.72	7.72	7.72
Mean price of all other goods & services	0.94	0.94	0.94

Table 17 lists the mean shares and prices for the three specifications of the 9-good system. Average mean prices for *dairy*, *food away from home* and *all other goods and services* remain unchanged in all specifications. *Dairy* had no products classified as high preparation and only one percent classified as low preparation so it makes sense that the mean price would remain fairly constant. *Food away from home* and *all other goods and services* prices were not changed by design. The added time cost specification consistently had the greatest prices, with the scaled specification in the middle. The groups of *produce* and *meat, eggs, seafood* had notably large price increases across the three specifications, each more than doubling in the added time cost specification reflecting their relatively large proportions of high and low preparation foods. Mean shares only had small changes between the standard and scaled specifications, but the added time cost specification had more notable changes in shares, again most prevalent for *produce* and *meat, eggs, and seafood*.

To compare the predictive capability of the three specifications and enable faster computation time, the sample was randomly divided in half (using the same seed) into a test set ($N = 59,307$) and training set ($N = 59,308$). The demand system was estimated using the training set and predicted values were calculated for all observations in both sets.

Mean squared error (MSE) measures the expected squared distance between an estimator and the true underlying parameter. Mean squared prediction error (MSPE) is mathematically the same measurement but is used for measuring values out of the original sample where the estimator acts like a prediction. Thus, MSPE measures the expected squared distance between what a predictor predicts for a specific value and the true value. Differences between the estimated values and true values were calculated the same way in both sets and are reported as MSE for the training set and MSPE for the test set.

16 Results

Table 18 lists MSE of the training set and MSPE of the test set for each food group in the three specifications.[11] Overall demand system log likelihood values for each specification are additionally reported at the bottom of Table 18. The log likelihood values can also be used as a measure of comparison since the observations are the same across all three specifications. The MSE and MSPE values are fairly consistent across the training and test sets suggesting that the estimator performs comparably both in and out of sample.

Table 18: Quality of estimate comparisons: mean squared error (MSE), mean squared prediction error (MSPE), and log likelihood for three specifications (standard prices, scaled prices, and prices with added time cost).

	Standard		Scaled		Added time cost	
	MSE	MSPE	MSE	MSPE	MSE	MSPE
Cereals and bakery	0.000179	0.000191	0.000179	0.000192	0.000239	0.000249
Produce	0.000224	0.000230	0.000226	0.000231	0.000545	0.000546
Meat, eggs, seafood	0.000391	0.000405	0.000421	0.000434	0.000682	0.000692
Dairy	0.000142	0.000149	0.000142	0.000149	0.000143	0.000151
Nonalcoholic beverages	0.000210	0.000202	0.000210	0.000202	0.000214	0.000206
Other food	0.001214	0.001183	0.001215	0.001184	0.001328	0.001295
Food away from home	0.000936	0.000984	0.000937	0.000985	0.000958	0.001008
All other goods & services	0.006874	0.007050	0.006927	0.007096	0.009240	0.009343
Log likelihood	1,113,224		1,089,521		1,017,204	

The standard system has the lowest error values as well as the highest log likelihood. The scaled system is similar to the standard as suggested by the similar shares and prices in Table 17. The added time cost specification has highest error values.

[11] MSE and MSPE are the same mathematical calculation which has a different name depending on whether the estimator is being evaluated in sample (MSE) or out of sample (MSPE).

Tables 19 through 21 separately display the income and price elasticities for each specification. Table 22 displays the income elasticities and own-price elasticities for the three specifications side-by-side.

The own-price elasticities in Table 19 fall in the range between the estimates of the two specifications in Okrent and Alston (2011): *cereals and bakery*, *meat, eggs, seafood*, and *dairy* were less elastic that in the model using BEA data and more elastic than the model using BLS data. *Produce* was slightly less elastic than both Okrent and Alston (2011) models; *nonalcoholic beverages* and *other food* were less elastic than the BLS data model and more elastic that the BEA data model.

Table 19: Income and uncompensated price elasticities, 8-goods, standard.

Elasticity of demand for:	with respect to price of:								
	Income	Cereals	Produce	Meat	Dairy	Drinks	Other	FAFH	AOGS
Cereals and bakery	0.49	-0.61	-0.07	-0.07	0.01	-0.02	-0.27	-0.04	0.58
(Cereals)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.05)	(0.02)	(0.07)
Produce	0.64	-0.08	-0.52	-0.09	-0.04	0.00	-0.06	-0.03	0.17
	(0.02)	(0.04)	(0.06)	(0.04)	(0.03)	(0.03)	(0.05)	(0.02)	(0.08)
Meat, eggs, seafood	0.51	-0.06	-0.07	-0.36	-0.06	-0.10	-0.21	-0.06	0.42
(Meat)	(0.03)	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)	(0.05)	(0.03)	(0.10)
Dairy	0.55	0.01	-0.04	-0.08	-0.78	0.06	-0.19	-0.02	0.50
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.05)	(0.02)	(0.08)
Nonalcoholic beverages	0.49	-0.03	0.00	-0.14	0.06	-0.88	0.01	0.01	0.49
(Drinks)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.03)	(0.09)
Other food	0.49	-0.11	-0.02	-0.09	-0.06	0.00	-0.70	-0.02	0.52
(Other)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)	(0.08)
Food away from home	0.99	-0.01	-0.01	-0.02	-0.01	0.00	-0.03	-1.01	0.10
(FAFH)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
All other goods & services	1.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-1.06
(AOGS)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Notes: Estimates of elasticities of demand were computed at the mean of the data. Standard errors are in parentheses.

Table 20: Income and uncompensated price elasticities, 8-goods, scaled.

Elasticity of demand for:	with respect to price of:								
	Income	Cereals	Produce	Meat	Dairy	Drinks	Other	FAFH	AOGS
Cereals and bakery	0.50	-0.56	-0.07	-0.08	0.02	-0.03	-0.27	-0.04	0.53
(Cereals)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.05)	(0.02)	(0.07)
Produce	0.64	-0.07	-0.55	-0.07	-0.02	0.01	-0.05	-0.02	0.14
	(0.02)	(0.04)	(0.06)	(0.04)	(0.03)	(0.02)	(0.05)	(0.02)	(0.08)
Meat, eggs, seafood	0.51	-0.06	-0.05	-0.34	-0.05	-0.10	-0.20	-0.07	0.35
(Meat)	(0.03)	(0.02)	(0.03)	(0.05)	(0.02)	(0.02)	(0.05)	(0.03)	(0.09)
Dairy	0.55	0.03	-0.03	-0.10	-0.78	0.06	-0.17	-0.02	0.46
	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.05)	(0.02)	(0.07)
Nonalcoholic beverages	0.50	-0.04	0.01	-0.17	0.06	-0.86	0.02	0.01	0.48
(Drinks)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.04)	(0.05)	(0.03)	(0.08)
Other food	0.49	-0.11	-0.02	-0.12	-0.05	0.01	-0.68	-0.02	0.50
(Other)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.05)	(0.02)	(0.07)
Food away from home	0.99	-0.01	-0.01	-0.03	-0.01	0.00	-0.03	-1.01	0.10
(FAFH)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
All other goods & services	1.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-1.06
(AOGS)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Notes: Estimates of elasticities of demand were computed at the mean of the data. Standard errors are in parentheses.

Table 21: Income and uncompensated price elasticities, 8-goods, time-cost.

Elasticity of demand for:	with respect to price of:								
	Income	Cereals	Produce	Meat	Dairy	Drinks	Other	FAFH	AOGS
Cereals and bakery	0.80	-0.31	-0.05	-0.16	-0.02	-0.13	-0.31	-0.06	0.24
(Cereals)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.05)
Produce	1.00	-0.04	-0.72	-0.03	-0.04	-0.03	-0.14	-0.06	0.06
	(0.02)	(0.02)	(0.04)	(0.03)	(0.01)	(0.02)	(0.03)	(0.02)	(0.05)
Meat, eggs, seafood	0.86	-0.11	-0.03	-0.65	-0.05	-0.07	-0.27	-0.10	0.41
(Meat)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.03)	(0.02)	(0.06)
Dairy	0.66	-0.05	-0.10	-0.16	-0.74	0.03	-0.14	-0.03	0.52
	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.06)
Nonalcoholic beverages	0.75	-0.21	-0.06	-0.15	0.02	-0.80	-0.16	0.01	0.60
(Drinks)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.04)	(0.02)	(0.07)
Other food	0.76	-0.15	-0.09	-0.19	-0.03	-0.05	-0.69	-0.04	0.48
(Other)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.04)	(0.02)	(0.05)
Food away from home	1.00	-0.02	-0.03	-0.05	-0.01	0.00	-0.03	-1.01	0.14
(FAFH)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
All other goods & services	1.03	0.00	0.00	0.01	0.00	0.01	0.01	0.01	-1.08
(AOGS)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Notes: Estimates of elasticities of demand were computed at the mean of the data. Standard errors are in parentheses.

Examining Table 22, none of the elasticities changed much between the standard and scaled specifications, which is not surprising given the similarities between the shares. There are some notable differences between the standard and added time cost specifications. Income elasticities went up for all at-home food groups in the added time cost specification with the most dramatic increases for *produce* and *meat, eggs, seafood.* The income elasticity for *produce* in the added time cost specification (1.00) indicates that group is on the threshold of being a luxury good. The own-price elasticities for *produce* and *meat, eggs, seafood* become more elastic in the added time cost specification as well. Other groups have mixed changes with some groups becoming less elastic in the added time cost specification (*cereals and bakery*, *dairy*, *nonalcoholic beverages*, and *other food*).

Table 22: Income and own-price elasticities for three specifications.

	Income elasticity			Own-price elasticity		
	Standard	Scaled	Added time cost	Standard	Scaled	Added time cost
Cereals and bakery	0.49	0.50	0.80	-0.61	-0.56	-0.31
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)
Produce	0.64	0.64	1.00	-0.52	-0.55	-0.72
	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.04)
Meat, eggs, seafood	0.51	0.51	0.86	-0.36	-0.34	-0.65
	(0.03)	(0.03)	(0.02)	(0.06)	(0.05)	(0.03)
Dairy	0.55	0.55	0.66	-0.78	-0.78	-0.74
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)
Nonalcoholic beverages	0.49	0.50	0.75	-0.88	-0.86	-0.80
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
Other food	0.49	0.49	0.76	-0.70	-0.68	-0.69
	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.04)
Food away from home	0.99	0.99	1.00	-1.01	-1.01	-1.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
All other goods & services	1.06	1.06	1.03	-1.06	-1.06	-1.08
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)

Notes: Estimates of elasticities of demand were computed at the mean of the data. Standard errors are in parentheses.

Table 23 further explores the income elasticities in the standard specification by income category and household size. Ordinal, mirrored trends are apparent across income categories and household size. As income category increases, income elasticities decrease for all at-home food groups, but increase for food away from home and all other goods. Conversely, as household size increases, income elasticities increase for all at-home food groups.

At the lowest income category, the income elasticities for *produce* and *meat, eggs, seafood* in particular were quite elastic with both groups nearly unit elastic. All other at-home food income elasticities were fairly elastic as well (≥ 0.89). At the highest income category, all at-home food categories were quite inelastic with *cereals and bakery* and *other food* actually showing negative income elasticities.

Table 23: Income elasticity by income and household size, 8-goods, standard.

Income elasticity	by income category:				by household size:			
	Very low	Low	Mid	High	1	2	3	4+
Cereals and bakery	0.90	0.74	0.39	-0.06	0.34	0.55	0.69	0.82
	(0.02)	(0.01)	(0.02)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Produce	0.97	0.82	0.58	0.34	0.57	0.67	0.73	0.83
	(0.02)	(0.01)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)
Meat, eggs, seafood	0.96	0.76	0.40	0.02	0.34	0.59	0.70	0.84
	(0.02)	(0.02)	(0.03)	(0.06)	(0.04)	(0.02)	(0.02)	(0.01)
Dairy	0.92	0.77	0.47	0.10	0.43	0.60	0.70	0.82
	(0.02)	(0.01)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)
Nonalcoholic beverages	0.89	0.73	0.39	0.02	0.37	0.55	0.64	0.78
	(0.03)	(0.02)	(0.03)	(0.06)	(0.03)	(0.02)	(0.02)	(0.02)
Other food	0.89	0.73	0.40	-0.03	0.39	0.53	0.64	0.76
	(0.02)	(0.01)	(0.02)	(0.05)	(0.02)	(0.02)	(0.02)	(0.01)
Food away from home	0.93	0.96	0.99	1.03	0.99	1.00	0.99	1.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
All other goods & services	1.02	1.05	1.06	1.07	1.06	1.06	1.05	1.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Estimates of elasticities of demand were computed at the mean of the data. Standard errors are in parentheses.

17 Discussion

The two new methods for integrating the cost of food preparation into a demand system add a new layer of insight, although both performed worse in predicting actual shares and explaining variation in the data than the standard prices. Scaling prices based on constant percentages for all consumers had relatively little effect as might be expected based on the "absence of money illusion" property of a demand system. By design, prices and expenditures were scaled to include a 30 percent time cost for at-home foods as a whole. Thus, while the prices and expenditures were not scaled at constant rate across all groups, the aggregation to these particular groupings produced a similar effect.

The wage-rate-dependent added time cost method was a direct extension of Mincer (1963) and the results indicated that actual demand might look different than standard demand system estimates if an additional opportunity cost of preparation time is factored in–especially for households with low discretionary income. However, the added time cost specification's very poor performance in explaining variation encourages caution in using those estimates for interpretation. If one's goal is to potentially improve upon prediction accuracy of demand system estimates by incorporating a time cost, a more rigorous approach should be taken to calibrating and testing parameters.

The income elasticities broken down by income category produced a set of interesting findings that support the need to assume non-linear Engel curves in demand systems. The income elasticities for all at-home food groupings decreased substantially as income increased, to the point that *cereals and bakery* and *other foods* were inferior for the highest income category on average. The food groupings *produce* and *meat, eggs, seafood* had the largest percentages of high and low preparation food, and they were the most income elastic for many consumers in the sample. This finding was intensified at lower discretionary incomes (low income or large household size). As in Part II, it is again not possible in the current study to distinguish if the preparation time characteristic plays a role in income elasticity or if the difference is mainly due to other product characteristics (e.g *cereals and bakery* differ from *meat, eggs, seafood* in terms of nutritional content, shelf-life, animal welfare concerns, etc.).

Part IV

Overall Conclusion

Household food production remains an integral part of daily life for most people despite substantial technological advances in the past several hundred years. Yet we are still bothered with related questions. Why are obesity rates so high and getting higher? Why do we make food choices we regret? Why do many people still go hungry in a country with an unprecedented level of steady food production? An undercurrent of judgment often accompanies these questions. Economics, however, is rooted in the assumption that people act rationally according to a set of logically consistent principles. While behavioral economics has shown that people often behave in predictably irrational ways, for practical purposes, the framework of economics can be a rather nonjudgmental way of looking at behavior. If we are not able to explain why people make certain food choices with our current models and we believe in rationality, then we must be missing something. We need to improve the theoretical models.

This dissertation is a first step to incorporating one factor into the models that is so pervasive it is almost invisible – the value of time. Time is impossible to control and difficult to properly value, but that does not mean we can just ignore its relevance.

The temporal discounting experiment (Part I) found that many participants exhibited constant discounting, some displayed present bias, and some actually displayed future bias. The results looked quite different for food rewards compared with money. Most participants preferred to make the food rewards about equal on the two distribution days. This "consumption smoothing" behavior was not seen with monetary rewards. These results suggest that people conceptualize food and money differently over time.

Perhaps people experience an additional component of utility that results from receiving food on two days that does not exist for money. Modeling and testing this hypothesis could be a productive line of future research–especially since the Convex Time Budget experimental framework is currently experiencing a great deal of active debate in the literature.

Also notable for healthy eating purposes is that overall, people did not display particularly impulsive behaviors for popcorn or chocolate in this choice framework. It is possible that the "present time" in the study was not immediate enough to trigger impulsive behavior. The in-person round had about a ten minute period separating the choices and distribution of popcorn. However, the big-picture goal of this research is not necessarily to contrive situations where people display present bias. Previous experiments have shown that people can behave impulsively and not in accordance with economically rational behavior. A more productive line of inquiry might be how we can use the consumption smoothing insight to improve healthy food choices. If a delay of only ten minutes is enough to avert impulsive food choices, then perhaps there is potential for some of the new methods of food procurement to have a positive impact on health. Online grocery ordering, meal kit delivery, and other online-based services temporally separate the food choice from consumption. It might be fruitful to see what impact these services will have over time and whether they will become accessible for all income levels.

The demand system incorporating leisure (Part II) added to the growing body of literature indicating a general shift towards more convenient foods as the opportunity cost of time increases. Among the sample of working, single-headed households, economic factors (income and household size) had much stronger implications for differences in food demand than social characteristics (gender, race/ethnicity). As consumers gain higher discretionary income, they become less responsive to the price of at-home food and more responsive to the shadow price of time.

These results also have implications for healthy eating strategies and can directly relate to the insights just mentioned. Both online grocery shopping and meal kit delivery are also acquisition/preparation-time saving innovations, and both tend to be relatively expensive. Since higher income consumers are particularly sensitive to the shadow price of time for at-home food demand, these new options for food procurement might be able to make an impact on their food choices. At current price levels, however, low income consumers are not likely to be able to take advantage of these new options.

Part II elasticity results for high and low preparation foods indicated that it might not be necessary to divide at-home foods in this way when incorporating leisure time as a good in the demand system. Other studies have found some support for the idea that the opportunity cost of time is already factored into the prices of at-home foods (Vickner, 2015). The results from Part III showed that the standard price model best fit the data out of the three specifications which might also be an indication that the opportunity cost of time is already factored in to at-home food prices. It is also possible that more robust parameter selection and testing could uncover scaled or added time cost specifications that would be a better fit as well.

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Appendix

Equation 29 lists the steps in the derivation of Equation 17 from modified Slutsky (Equation 14). The derivation of the standard elasticity forms (Equation 16) follows the same pattern but without the last terms. Start with the (modified) Slutsky equation and multiply each term by $\frac{w}{Q_i} \cdot \frac{M}{M}$. Rearrange terms, then substitute using the definition of full income, $M \equiv v + wT$. If non-wage income is assumed to be zero, $(v = 0)$, then $\left(1 - \frac{v}{M}\right) = 1$, and the equation simplifies to the elasticity form.

$$
\begin{aligned}
\frac{\partial Q_i}{\partial w} &= \frac{\partial Q_i}{\partial w}\Big|_u - t_l \frac{\partial Q_i}{\partial M} + T \frac{\partial Q_i}{\partial M} \\
\underbrace{\frac{\partial Q_i}{\partial w}(\frac{w}{Q_i}}\frac{M}{M}) &= \underbrace{\frac{\partial Q_i}{\partial w}\Big|_u (\frac{w}{Q_i}}\frac{M}{M}) - t_l \frac{\partial Q_i}{\partial M}(\frac{w}{Q_i}\frac{M}{M}) + T \frac{\partial Q_i}{\partial M}(\frac{w}{Q_i}\frac{M}{M}) \\
\varepsilon_{it_l} &= \varepsilon_{it_l}^{compensated} - \underbrace{\frac{wt_l}{M}}\underbrace{\frac{M}{Q_i}\frac{\partial Q_i}{\partial M}} + \underbrace{\frac{wT}{M}}\underbrace{\frac{M}{Q_i}\frac{\partial Q_i}{\partial M}} \\
\varepsilon_{it_l} &= \varepsilon_{it_l}^{c} - s_{t_l}\varepsilon_{Q_i}^{M} + \left(1 - \frac{v}{M}\right)\varepsilon_{Q_i}^{M} \\
\varepsilon_{it_l} &= \varepsilon_{it_l}^{c} - s_{t_l}\varepsilon_{Q_i}^{M} + \varepsilon_{Q_i}^{M}
\end{aligned}
\tag{29}
$$

Table 24: ATUS time codes to create time use groups "market work," "leisure," and "housework."

Market work	Leisure	Housework
Working except job search	Socializing, relaxing, leisure	Household activities
t050189 t050101-t050103	t120199 t120101	t020199 t020101-t020104
t050289 t050201-t050204	t120299 t120201-t120202	t020299 t020201-t020203
t050389 t050301-t050304	t120399 t120301-t120313	t020399 t020301-t020303
t059999	t120499 t120401-t120405	t020499 t020401-t020402
Related travel	t120599 t120501-t120504	t020599 t020501-t020502
t180589 t180501-t180502	t129999	t020699 t020681
	Sports, exercise, recreation	t020799 t020701
	t130199 t130101-t130136	t020899 t020801
	t130299 t130201-t130232	t020999 t020901-t020905
	t130399 t130301-t130302	t029999
	t130499 t130401-t130402	Caring for and helping hh
	t139999	t030199 t030101 t030108
	Volunteering	t030109 t030111 t030112
	t150199 t150101-t150106	t030299 t030201-t030204
	t150299 t150201-t150204	t030399 t030301-t030303
	t150399 t150301-t150302	t030499 t030401-t030405
	t150499 t150401-t150402	t030599 t030501-t030504
	t150599 t150501	t039999
	t150699 t150601-t150602	Caring for and helping nonhh
	t159989	t040199 t040101 t040108
	Fun activities with kids	t040109 t040111 t040112
	t030110 t030102-t030105	t040299 t040201-t040204
	t040110 t040102-t040105	t040399 t040301-t040303
	t030186	t040499 t040401-t040405
	t040186	t040599 t040501-t040508
	Related travel	t049999
	t181283	Grocery shopping
	t181299 t181201-t181202	t070101
	t181399 t181301-t181302	Purchasing food (not groceries)
	t181204	t070103
	t181599 t181501	Related travel
		t181199 t181101
		t180280
		t180399 t180381-t180382
		t180499 t180481-t180482
		t180701

Table 25: Subset (a) of parameters from 5-good estimation system (alpha, beta, gamma, lambda).

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
alpha_1	-0.078	0.047	-1.65	0.098	-0.171	0.014
alpha_2	-0.093	0.224	-0.42	0.677	-0.532	0.346
alpha_3	-0.699	0.136	-5.14	0.000	-0.965	-0.432
alpha_4	3.027	0.419	7.22	0.000	2.206	3.848
alpha_5	-1.157	0.270	-4.29	0.000	-1.686	-0.628
beta_1	-0.004	0.002	-1.75	0.080	-0.008	0.000
beta_2	-0.009	0.011	-0.88	0.379	-0.030	0.012
beta_3	-0.037	0.006	-5.85	0.000	-0.049	-0.024
beta_4	0.094	0.018	5.24	0.000	0.059	0.129
beta_5	-0.044	0.012	-3.69	0.000	-0.067	-0.020
gamma_1_1	0.003	0.000	7.99	0.000	0.002	0.004
gamma_2_1	0.000	0.001	-0.06	0.953	-0.002	0.002
gamma_3_1	0.003	0.002	1.89	0.059	0.000	0.006
gamma_4_1	-0.006	0.004	-1.33	0.182	-0.014	0.003
gamma_5_1	0.000	0.002	-0.01	0.994	-0.004	0.004
gamma_2_2	0.017	0.004	3.93	0.000	0.009	0.026
gamma_3_2	0.009	0.007	1.31	0.190	-0.005	0.023
gamma_4_2	-0.005	0.019	-0.25	0.806	-0.043	0.033
gamma_5_2	-0.022	0.008	-2.77	0.006	-0.037	-0.006
gamma_3_3	0.025	0.008	3.00	0.003	0.009	0.041
gamma_4_3	-0.052	0.016	-3.20	0.001	-0.084	-0.020
gamma_5_3	0.015	0.008	1.88	0.060	-0.001	0.032
gamma_4_4	0.199	0.057	3.51	0.000	0.088	0.310
gamma_5_4	-0.136	0.030	-4.57	0.000	-0.194	-0.078
gamma_5_5	0.142	0.018	8.01	0.000	0.107	0.177
lambda_1	0.000	0.000	-1.70	0.090	0.000	0.000
lambda_2	0.000	0.000	-0.91	0.364	0.000	0.000
lambda_3	0.000	0.000	-5.82	0.000	-0.001	0.000
lambda_4	0.001	0.000	4.02	0.000	0.000	0.001
lambda_5	0.000	0.000	-1.32	0.187	0.000	0.000

Notes: Standard errors adjusted for 10,001 clusters in household_code

Table 26: Subset (b) of parameters from 5-good estimation system (eta, rho).

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
eta_sex_1	0.000	0.000	1.54	0.122	0.000	0.000
eta_sex_2	0.000	0.000	1.16	0.246	0.000	0.000
eta_sex_3	0.000	0.000	12.45	0.000	0.000	0.000
eta_sex_4	-0.002	0.000	-16.79	0.000	-0.002	-0.002
eta_sex_5	0.001	0.000	18.22	0.000	0.001	0.002
eta_hh_size_1	0.000	0.000	-14.95	0.000	0.000	0.000
eta_hh_size_2	0.000	0.000	-16.91	0.000	0.000	0.000
eta_hh_size_3	0.000	0.000	0.29	0.774	0.000	0.000
eta_hh_size_4	0.000	0.000	5.79	0.000	0.000	0.000
eta_hh_size_5	0.000	0.000	0.65	0.519	0.000	0.000
eta_region_1	0.000	0.000	1.19	0.235	0.000	0.000
eta_region_2	0.000	0.000	1.41	0.160	0.000	0.000
eta_region_3	0.000	0.000	-1.13	0.259	0.000	0.000
eta_region_4	0.000	0.000	-0.68	0.495	0.000	0.000
eta_region_5	0.000	0.000	0.44	0.657	0.000	0.000
eta_kids_1	0.000	0.000	4.92	0.000	0.000	0.000
eta_kids_2	0.000	0.000	0.87	0.383	0.000	0.000
eta_kids_3	0.000	0.000	-0.38	0.707	0.000	0.000
eta_kids_4	-0.001	0.000	-5.69	0.000	-0.001	0.000
eta_kids_5	0.001	0.000	5.94	0.000	0.000	0.001
eta_age_cat_1	0.000	0.000	0.72	0.474	0.000	0.000
eta_age_cat_2	0.000	0.000	0.75	0.454	0.000	0.000
eta_age_cat_3	0.000	0.000	21.45	0.000	0.000	0.000
eta_age_cat_4	-0.001	0.000	-13.80	0.000	-0.001	-0.001
eta_age_cat_5	0.000	0.000	10.75	0.000	0.000	0.001
eta_race_hisp_1	0.000	0.000	-4.56	0.000	0.000	0.000
eta_race_hisp_2	0.000	0.000	-1.89	0.059	0.000	0.000
eta_race_hisp_3	0.000	0.000	-5.10	0.000	0.000	0.000
eta_race_hisp_4	0.001	0.000	11.25	0.000	0.001	0.001
eta_race_hisp_5	-0.001	0.000	-11.53	0.000	-0.001	-0.001
rho_sex	0.001	0.001	1.61	0.108	0.000	0.002
rho_hh_size	0.000	0.000	-1.50	0.132	-0.001	0.000
rho_region	0.000	0.000	0.27	0.788	0.000	0.000
rho_kids	0.002	0.001	1.76	0.078	0.000	0.004
rho_age_cat	0.001	0.000	1.43	0.153	0.000	0.002
rho_race_hisp	-0.250	0.000	-932.20	0.000	-0.251	-0.250

Notes: Standard errors adjusted for 10,001 clusters in household_code