Limited Attention and the Deadline Effect: Simple Spending Rules in the Field

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Abstract[1]

We examine behavior in a dynamic planning problem in a residential community which serves as an arguably clean field context for estimating spending rules. Surveying a sample of program participants about their spending plans, we find that spending smoothly is the most frequently preferred plan. In examining actual spending data, participants vary widely in terms of their implementation of such a plan. An increasing fraction of participants begin to smooth their spending as the program's expiration deadline nears. We claim that the explanation for this pattern is limited attention to the planning task, which we identify by classifying participants' spending rules and estimating structural breaks in which participants switch into smoothing their spending for at least two weeks in a row.. Limited attention participants are economically influential, responsible for driving the bulk of retail sales growth in the last month of the year. Our results suggest that imposing deadlines may be helpful towards individuals' dynamic planning tasks.

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1. Introduction

How individuals approach dynamic planning problems lies at the heart of countless important economic decisions – examples of which are household retirement planning and life-cycle consumption, as well as the use of flexible spending and health savings accounts, food stamp programs, tax rebates, gift cards and debit cards. Identifying psychological influences on consumer spending rules using large-scale household survey data is challenging, due to the confounding influences of individual life circumstances and structural uncertainties in most dynamic decision environments in the field. Given this reality, it can be useful to detect basic behavioral anomalies in dynamic planning using clean and simple field environments where possible.

This paper analyzes data from a university residential community which serves as an arguably simple and clean such field setting, studying how individuals dynamically allocate their spending choices in a straightforward finite horizon planning problem enforced by an expiration deadline. Program participants tend to state a preference for smoothing their spending within the program evenly over the program horizon, in accordance with the economically intuitive approach to the planning problem. Yet in spite of a general stated desire to smooth spending, participants vary widely in terms of *when* they actually start implementing this plan. Participants are increasingly likely to start implementing smoothing as the program's expiration deadline nears. We claim that limited attention to the planning problem is the most plausible explanation for this behavior, and we estimate a simple structural decision model to support this hypothesis.

We consider four simple spending rules for each participant: 1. smoothing with weekly updating; 2. smoothing with a personal bias; 3. limited attention and 4. the school's suggested plan. We then statistically classify program participants by the ability of each spending rule to explain their personal spending pattern. Although limited attention types comprise less than 25% of all participants in our sample, they are highly influential in the aggregate. Retail sales double on a weekly basis during the final three weeks before the program's expiration deadline. This deadline effect is overwhelmingly driven by the net increase in spending by estimated limited attention participants: those program participants who significantly switch from some personal natural spending bias to dividing their current balance evenly by the number of remaining weeks.

The fraction of participants in the program switching into the complete smoothing rule for spending increases steeply in a monotonic fashion as the expiration deadline approaches. Since we are using field data, we do not have the ability to experimentally test the causal effect of the deadline. However, the distribution of switching weeks across heterogeneous participants can only be plausibly explained by some common incentive in the decision environment. A detailed examination of participants' behavior strongly suggests the deadline as the common incentive (see also Ariely and Wertenbroch, 2002 which discusses the effect of deadlines on academic work).

Our intuitive finding is that a significant fraction of individuals pay more attention to dynamic planning only when it becomes crucial for them to do so, such as in the case of a significant pending welfare loss. What makes the evidence supportive of an attention-based explanation is not merely the fact that individuals' spending adjusted in the individually appropriate direction over time. Rather, in identifying attention, the way the adjustments were made need to satisfy two crucial features: 1. Sudden adjustment rather than gradual (sufficient to estimate a statistically significant structural break in spending rules implemented over time); 2. Smoothing behavior in the weeks immediately before the deadline. Without this second feature, alternative explanations such as precautionary saving (in the case of increasing spending profiles), and budget constraints or time discounting (in the case of decreasing spending profiles) might be likely. In addition, we do find limited attention participants who adjusted their spending behavior downward in addition to those who adjusted spending upward near the deadline.

These observations may be interpreted as a baseline approximation of natural behavior in a dynamic spending setting in the absence of the many complexities of real life spending and investment decisions. Furthermore, since program participants are approximately the age at which most new labor market participants begin making independent savings and spending decisions, the results are also suggestive of the natural approach that young adults may take in medium to long-term dynamic planning problems. Such natural tendencies may be difficult to elicit in a laboratory setting where well-defined optimization problems are usually suggested to subjects. The residential program provides an opportunity to observe natural responses to dynamic planning in a field setting where the classical prediction is so simple and economically intuitive that participants do not need to think very hard or solve anything in telling us how they wanted to spend their plan.

Our paper is closely related to the literature on bounded rationality in dynamic savings and consumption. This literature has frequently been motivated by the question of whether the permanent income hypothesis adequately accounts for households' consumption behavior. Reis (2006) presents a model in which consumers rationally choose to only occasionally update the information relevant to their consumption decision due to costs of planning. Sims (2003) and Moscarini (2004) model information processing constraints, where agents devote only limited attention to observing the values of relevant state variables in the decision problem. Survey work by Lusardi (1999, 2003), and Ameriks, Caplin, and Leahy (2003) provide empirical evidence that some households make financial plans rather infrequently. Madrian and Shea (2001) document that participation rates in 401k plans are distinctly increasing in employee age. Our findings suggest that lack of attention of younger people to their retirement plans may be a main influencing factor. Binswanger and Carman (2012) show that households claiming a rule of thumb approach to savings, such as having a monthly savings target, save approximately as much as households who claim to be actually looking forward and planning for their retirement. Brown, Camerer and Chua (2009) experimentally examine subjects' learning in a complex, laboratory-based dynamic savings and consumption environment, finding evidence for bounded rationality.

This study also contributes to the literature examining the effects of consumer inattention on product demand, following the framework proposed by Dellavigna (2007). Chetty, Looney and Kroft (2009) conduct a field experiment which finds that sales tax salience reduces product demand at grocery stores – the rationale being that when taxes are less salient, consumers pay less attention to the tax component of the total price. Lacetera, Pope and Sydnor (2012) study the effect of left-digit bias in odometer readings on the used car market. They find discrete drops in selling prices for used cars with odometer readings at exact intervals of 10,000 and 1000 miles. They trace this discontinuity of market prices to limited attention, and confirm in an experiment that people are more likely to recall the left most digit in an odometer context compared to any other digit. Other recent work addressing inattention includes Finkelstein (2009) on road toll salience, Hossain and Morgan (2006) on shipping fees, Lee and Malmendier (2011) on eBay bidding, and Pope (2009) on hospital rankings. This paper supports this growing body of empirical micro-level evidence that individuals do not pay full attention to relevant information at all times, and further proposes time-salience as a driving factor in re-directing individuals' attention and changing behavior towards what is predicted by classical economic theory.

Our study differs in focus compared to the work of Stephens (2003), Shapiro (2005), and Hastings and Washington (2010), which study the food consumption dynamics of households receiving public assistance. They find that households on public assistance tend to spend more than what a standard life-cycle model predicts, directly after having the money at their disposal, with non-standard time discounting as one explanation. Although our study is similar to theirs in the goal of studying dynamic spending and consumption in the field, the behavioral explanation we find is different. This is due to the different characteristics of population types, in the sense their subjects are more likely to be constrained by impatience and limited monetary resources, while our subjects are more likely to be most constrained by attention in this particular setting.

We supplement the empirical work on actual spending data with a survey of the program's participants, although in a different program year than our spending data, in order to gain a sense of participants' self-reported intended spending plans.[2] The survey responses provide evidence against the alternative hypothesis that participants increased their spending at the end of the year due to a desire to purchase durable goods at the end of the year. The survey evidence also refutes time discounting as a primary explanation for the dynamic spending patterns observed, since very few participants stated the desire to have either an upward or downward trend in their spending. The survey is the only data we have which give any information about demographic characteristics, and shows that spending intentions did not vary systematically by any observable demographic characteristics.

The remainder of the paper is organized as follows: Section 2 describes the residential program, data and motivating aggregate facts; Section 3 describes the models of spending behavior; Section 4 estimates individual spending profiles and statistically classifies each participant; Section 5 examines limited attention participants in greater detail, including their macro-effect; Section 6 addresses possible alternative explanations for the observed spending behavior including a discussion of the survey results; Section 7 concludes.

2. Data and Empirical Facts

The data are comprised of participant level transactions from a residential program at a large public university in the United States in the 2005 – 2006 academic year. The program is part of the university's room and board contract, so that students who live on-campus must also purchase 1800 meal points. These meal points can be used at several dining facilities around the campus, which are located directly next to residence halls. One meal point is equivalent to a dollar in purchasing power, and points are stored electronically on the participant's ID card. The ID card functions as a debit card in keeping track of participants' expenditures and remaining balance, among other unrelated uses.[3] With few exceptions, all participants of the meal plan are 1st or 2nd year undergraduate students.[4] Unfortunately, our data do not have any demographic information of participants, including their school year – so we are unable to analyze the impact of experience on the planning task.

Each time a participant makes a purchase with meal points, his/her remaining account balance is displayed on the cash register. Participants may also look up their account balances online at any time. Although the cost of acquiring knowledge about one's balance is low and only requires looking at the register display after any purchase, it is entirely possible to not be devoting actual attention to this information from a dynamic decision-making standpoint. Indeed, experiments by Simons and Chabris (1999) and others in the cognitive psychology literature show that humans are strikingly prone to "inattentional blindness" towards clearly visible phenomenon when concentrating on unrelated tasks.

[2] Since the survey of participants' intended spending plans was conducted in a later year than the year of the spending data itself, we cannot do any empirical work that would require the two data sets being connected. We use the survey results as an approximation of likely factors influencing spending decisions in an identically structured program. Details of the survey are provided in Section 6 and Appendix D.

[3] For example, students need their ID card to enter gym facilities, for taking exams, and also have the capability to use it as a general campus debit card to store money for fast-food, laundry and other campus expenses. The general debit card function is completely separate from the official meal plan in that there is no expiration deadline for money placed in the debit program, and refunds for money deposited in the debit card are given at any time.

[4] The exception is one dormitory on-campus which accepts a small number of upper level undergraduates and graduate students as residents.

The deadline for using points is the end of the academic year, with the program lasting 33 weeks. We exclude inter-quarter breaks and other holidays when facilities were closed. After the deadline, any remaining meal points are non-refundable, and therefore expire if they are not spent. Participants are clearly informed of this rule at the beginning of the program, and are provided with a schedule of recommended point usage upon moving into their residences. As the expiration deadline draws nearer, participants are reminded of the deadline via signs posted in residence areas.

Participants may purchase a variety of items with their meal points, ranging from cafeteria food, perishable and non-perishable snacks, to items that may be useful in the dormitory, such as cooking appliances, batteries, and school supplies. Every residence hall complex has an associated adjacent dining facility, which makes spending meal points convenient. Dining facilities at this university receive generally positive reviews from students on online rating websites regarding the quality of the food, comparable with the reviews for nearby off-campus restaurants. The campus also houses one brick and mortar convenience store where students may purchase supplies, snacks and dormitory items, as well as an affiliated online store where students can order on the internet and have items delivered to their dormitories. Appendix A provides a partial listing of the types of items offered in these stores. Note that the items offered and their prices are constant over the course of the program, as are the prices of dishes in the cafeterias.

Using the university residential program in examining dynamic planning behavior is advantageous for the following reasons: 1. The pre-paid account expires at the end of the academic year with certainty, and program participants are informed clearly of this fact at the start of the program; 2. Prices and availability of goods in the program do not change over the horizon of the plan; 3. The pre-paid account is intended for campus residents' daily use within the university campus, for food and residential items, which makes spending from the account convenient and easily incorporated into a weekly routine. Thus, the major complexities which can make most other "real life" dynamic planning tasks difficult (including in the typical life-cycle consumption and savings problem) are substantially simplified or even absent in this setting. It is these structural simplifications that make limited attention possible to detect in our field data, where it would be likely difficult to otherwise detect using household survey data.

Our survey was conducted one year after the data was collected, because we wanted to know more about participants' motivations and how they viewed their spending plans. We cannot connect the survey data to the actual spending data, since the survey sample and spending data sample are from different individuals. A detailed description of the survey and results, including demographic information (gender, major, year in program) is provided in Section 6 and Appendix D.

A brief summary of the survey results is as follows: 42% of respondents said they wanted to spread their meal point usage evenly over time, while 17% said that they actually ended up doing so. 1% of respondents said they had wanted to spend more meal points earlier in the year, and 11% said they actually ended up doing so. 10% of respondents reported intending to spend more points later in the year, and 16% of respondents reported doing so. 0% of respondents reported wanting to spend more in the middle of the year, and 6% reported actually doing so. Finally, 44% of respondents reported wanting to spend as necessary, and the same fraction reported actually doing so.[5] These responses are generally consistent with our empirical findings the spending data, although we do not wish to infer too much meaning from the exact proportions reported.

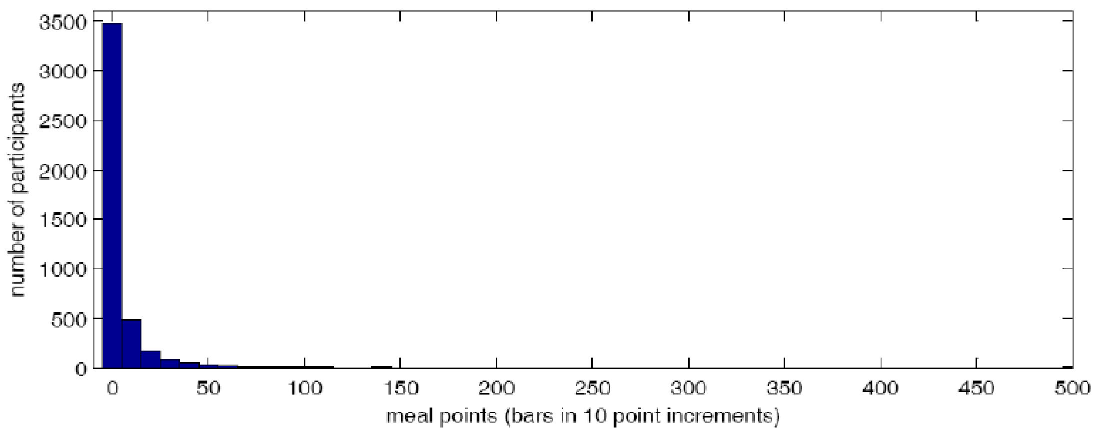
It is helpful to have some idea of how meal points factor into students' overall pocket money in an academic year. While there is inevitably some heterogeneity among student resources and expenses, we know the following facts about the participant population: 1. The university-provided

[5] One possible interpretation is that some of the 'as necessary' spenders could be limited attention participants who have not yet started paying attention to the planning task.

estimate for undergraduate "spending money" is lower than the allotted meal point budget in dollar terms, meaning the university officially sets some expectation among students and parents that the meal plan should be covering more than half of day-to-day living expenses for students;[6] 2. Among students who were on the meal plan that year, 76% of them were receiving some form of financial aid, where the university policy uses federal standards to determine student need based on family resources. Furthermore, 96% of aid provided at the university is solely needs-based rather than using any other criteria.[7] These facts together provide an ex-ante convincing case that students on average, do not have such ample access to financial resources that they simply do not care about their meal plan use. The meal plan, whose total value is $1800, represents a significant fraction of their yearly spending.

The data from the ex-post perspective also support the claim that students valued the meal plan. Figure 1 below shows the distribution of 'expired' meal points by participant in our sample. The great majority of participants used all of their meal points, with less than 70 participants (ie. less than 2% of the sample) leaving more than 100 meal points to expire.

Figure 1: Distribution of expired meal points, by participant



The modal participant in the sample consumed between one-third and one-half of their total meals within the plan. Details about how this figure was calculated and some relevant histograms are provided in Appendix B. When breakfast meals are excluded, the proportion of meals consumed in the plan rises to about one-half. Altogether, the modal expenditure for a meal in the plan was 6 meal points, which is equivalent to $6.

The effects of limited attention in the aggregate can be seen most clearly from Figure 2, which shows the time trend of retail purchases in our sample. We define a *retail purchase* as a transaction that is over $20 made at locations which do not serve prepared meals – these locations specialize in the sale of more durable goods, such as non-perishable foods, supplies and equipment. This is a lower bound on the actual number of 'retail purchases', since purchases of similar goods can be made on a small scale in other locations as well, but those are not counted here. The magnitude of this retail trend is unaffected by the sample selection, as shown later in Figure 3 (top panel).[8,9]

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6 Specifically, the estimate for "spending money" was given at $1341 for year 2011-2012 (excludes books and supplies, tuition/fees, transportation, medical insurance which were listed as separate categories). The year that the data was collected, the estimate was likely to be lower due to inflation.

7 Depending on the individual student aid package, financial aid can include scholarship, loan, and/or work-study.

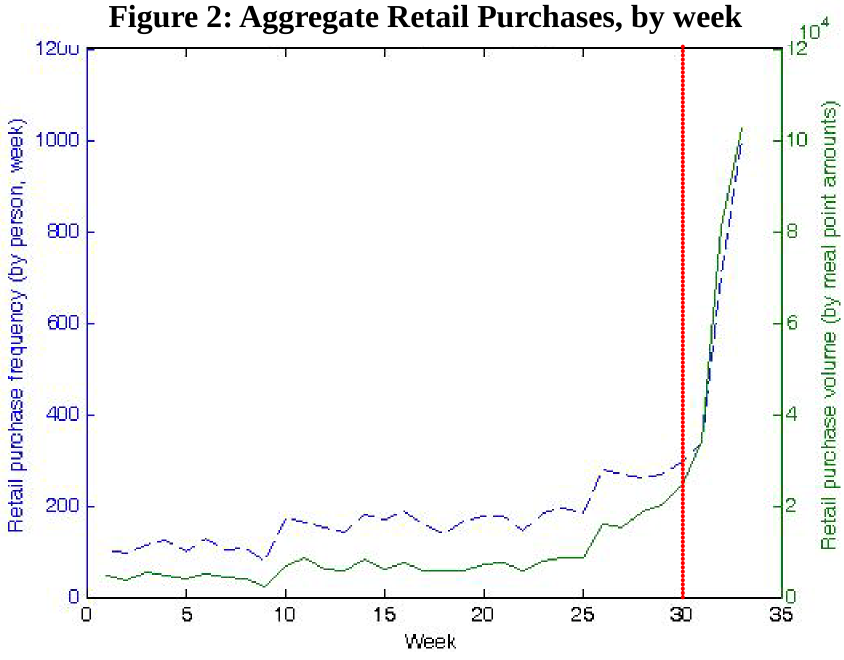
8 This measure of retail purchases is designed to measure non-meal spending occurring in the program. The current definition of "retail sales" is based on the assumption that $20 is a reasonable upper bound for money spent on a single meal. Figure 2 is also robust to changes in the definition of retail sales.

9 Total (including non-retail) purchases also display a sharp increase in the final weeks of the program: a combination of

From week 30 to week 33, weekly retail purchases (in terms of both volume: right axis, and frequency: left axis) on average more than doubled on a week-on-week basis. Additionally, retail sales also experienced substantial growth at the end of week 10, as the end of the first academic quarter approached.[10] We propose that these two episodes of retail sales growth are driven by the salience of the expiration deadline in particular weeks in the program. The week 10 increase was due to some participants for whom the end of the first quarter reminded them of the eventual expiration date, prompting them to revise their plans accordingly. The week 30 to week 33 increase was a response to a combination of time proximity and university posted reminders, which made the week 33 deadline more salient, prompting higher spending in the weeks immediately prior to the deadline. The distribution of structural breaks among participants statistically best explained under the limited attention model in fact follows this time trend of retail purchases closely.

The drastic increase in retail purchases is economically significant for a couple of reasons: First, the retailer needs to plan ahead for such a growth rate in transactions volume, by ensuring that inventories are appropriately stocked.[11] Additionally, if there is a probability that retailers have not in fact perfectly anticipated the growth in retail sales volume by stocking their inventories correspondingly, consumers (ie. plan participants) would like to plan ahead for this growth in sales activity by making their retail purchases before other consumers exhaust the supply of desired products. Finally, note that the dollar amount equivalents of the retail transactions are substantial, with year-long retail transactions worth over half a million dollars, and about half of that amount occurring in the last 4 weeks of the program.

Figure 2: Aggregate Retail Purchases, by week



We focus on identifying patterns of how individuals spend out of pre-paid accounts, rather than the decision of whether or when to deposit more money into their accounts. Thus, we drop program participants who at some point during the program time horizon had to consider whether and when to deposit more money into their account.[12] The decision problem of participants who added additional

increase in durable purchases and an increase in perishable cafeteria purchases as shown in Figure 3.

[10] In fact, the week-on-week growth was highest in week 10 at 185% growth, followed by week 32 at 129% growth.

[11] In the case of a non-profit maximizing retailer, logistical concerns such as having to respond to customer inquiries would also motivate the desire to plan ahead for the increase sales volume.

[12] One reason being that any additional money deposited into the account is also subject to the expiration deadline, so that in the presence of any uncertainty, depositing additional funds into the pre-paid account entails a risk which must be

money to their account is substantially more complex, and presents a data problem in that we do not observe those participants' spending pattern *unless* they do decide to deposit more money into the account.[13] In particular, our method for detecting limited attention via structural breaks in spending, will not work for individuals who had the need to add more money to their plan. After dropping these individuals from the sample, every participant in the empirical analysis is essentially facing an identical problem: how to spend 1800 meal points over an academic year.

Due to this sample censoring procedure, the interpretation of the empirical results should keep the structural asymmetry of the decision problem in mind. The current data do not allow us to estimate the overall proportion of limited-attention spending in dynamic settings, and we do not believe that any proportions of planning types found necessarily carry over to other populations. We can only conclude that at least a *sizeable* fraction of total participants exhibited a structural break in their spending patterns in this program – and the distribution of such structural breaks among those participants, is consistent with a limited attention hypothesis induced by the presence of a deadline. Further, since the data are censored only in one direction, our primary message is not about under-spending or over-spending per se – but rather to point out the significance and magnitude of effects that limited attention can have on spending environments.

The charts in Figure 3 below show that our sample selection criteria of dropping participants who finished meal points early has little effect on the aggregate retail volume trend. The top-most panel in Figure 3 is identical to Figure 2, but plots retail volume for *both* sample (blue dotted) and total (red, includes dropped) participants. The difference between total participants and sample is small and has been magnified for the reader in the second panel from the top – the difference between the two samples shows no discernable trend.

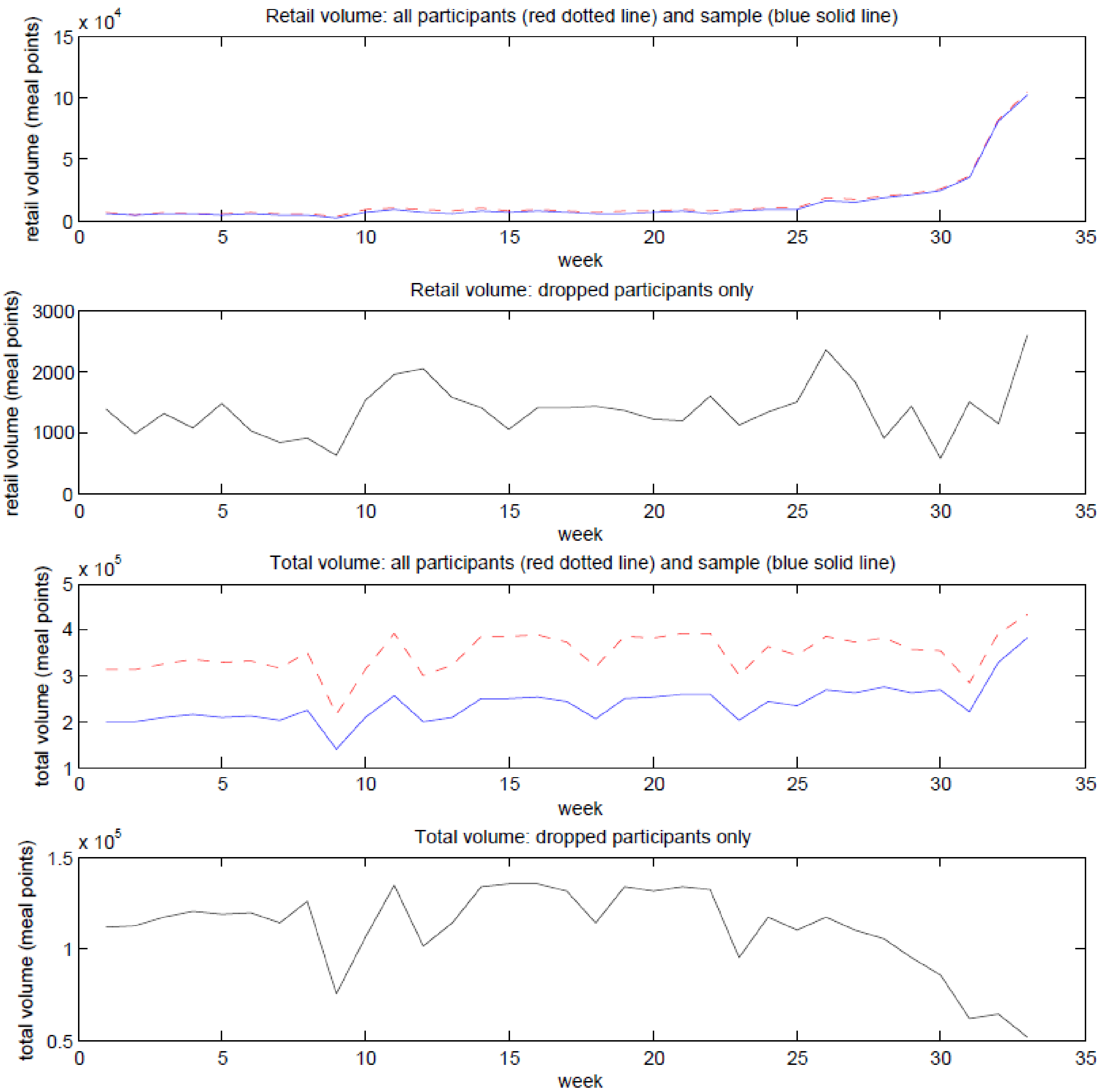
By contrast, the dropped program participants do contribute substantially to the total volume of sales (retail plus meal, 3rd panel), and that contribution understandably declines over time (bottom-most panel). Thus the phenomenon of drastic retail purchase growth which we want to explain in Figure 2 is robust to the sample selection.

For each program participant, we can observe the amount of the transaction, the facility where the transaction took place, and the date and time stamp of the transaction. We do not observe the names of exact items being purchased with the account, nor any specific demographic characteristics of the participants. Appendix D shows that in the survey at least, there was minimal variation in reported spending plans across demographic characteristics. We aggregate the data within-participant at the weekly level in order to obtain individual-level weekly expenditures. This serves to reduce eliminate daily noise created by day-of-the-week effects.

traded off with the discount offered. There is a discount associated with depositing additional money into the account: every 100 dollars deposited at a time yields 120 meal points. Alternatively, a participant can pay cash for any of the items in the program and forgo this discount, but not risk having to spend more than needed.

[13] This includes those students who at any point in time *actually* deposited more money into their account as well as participants who depleted their 1800 pre-paid points before the final week and did not refill their account. The total number of program participants was 6310, and 1839 (slightly less than 30%) were removed from the sample under either of these criteria. About two-thirds of these 30% had purchased additional points.

Figure 3: Comparison of aggregate trends for all participants versus sample participants



3. Decision Problem and Spending Rules

We consider four spending rule solutions to the problem of how to spend from the account: *smoothing with updating* (abbreviated SU), *personal bias* (abbreviated PB), *limited attention* (abbreviated LA), and *suggested plan* (abbreviated SP). For both realism and simplicity, we assume perfect information to reflect the fact that there is in reality, little external uncertainty in this simple spending decision.[14] We also abstract from time discounting for simplicity, and because it is likely that the discount factor for the types of items sold in the plan should be close to one.[15] This simplifying assumption appears to be consistent with survey responses among plan participants, in which very few participants intended to use more points in early periods compared to later periods,

[14] Uncertainty about own future spending preferences based on available goods should disappear quickly over time since the goods offered and their prices are fixed over the year. Partial plans and refunds are available for those students who are not academically enrolled for part of the academic year. However, dropping out mid-year is a rare occurrence. We discuss uncertainty as a possible alternative explanation for observed behavior in Section 6 and argue that uncertainty alone is unlikely to generate the spending profiles that produce the aggregate pattern in Figure 2.

[15] Including time discounting in the model generally does not help to explain the aggregate result in Figure 2, since the nature of the time trend in retail sales is in fact due to discrete individual switching in decision rules.

or alternatively intended to use more points in later periods compared to early periods.

Our analysis assumes that consumers may *potentially* be fully forward looking in their planning horizon, but that they myopically assume they can implement their intended spending plan in the next period without error. This reflects the fact that consumer choice of spending amounts in this setting is easy to implement - thus it is reasonable to assume that consumers do not consider the uncertainty arising from possibly not being able to accurately implement their own intended future action as a significant source of uncertainty in making their dynamic plan.[16] Once the next period arrives, participants may re-optimize their plan to accommodate ex-post spending 'mistakes' that have occurred.

We allow for participants to be at least partially inattentive to state variables in the dynamic planning problem, approximating their behavior using a personal bias parameter λ which captures their individual tendency to 'over-spend' or 'under-spend'. We then empirically estimate at which weeks in the program participants choose to start updating their plans fully, and use statistical model selection criteria to determine whether the estimated regime change significantly helps to explain observed behavior or not. Each spending rule is estimated at the individual participant level.

We formulate the <u>general decision problem</u> of the participant is as follows: In *each* period (signifying one week) t = 1 to T, the perfectly attentive, *smoothing with updating* (SU) consumer solves

$$\underset{\{s_{n,t},m_{n,t}\}_{t=\tau}^{T}}{Max} \sum_{t=\tau}^{T} U_n(s_{n,t}, m_{n,t}) \tag{1}$$

subject to the two budget constraints

$$W_{n,t} = W_{n,t-1} - s_{n,t} \tag{2}$$

$$M_{n,t} = M_{n,t-1} - m_{n,t} \tag{3}$$

where $s_{n,t}$ is spending of *meal points* in week t by participant n; $m_{n,t}$ is spending of *cash* in week t by participant n; and $W_{n,t-1}$ is given.[17] $W_{n,t-1}$ denotes the current stock of meal points, where $W_{n,1}$ is given, and $W_{n,T} = 0$. $M_{n,t-1}$ denotes the current stock of cash.[18] $U_n(\cdot)$ is participant n's utility of meal point and cash spending, which we assume is quasi-linear in cash, so that $U_n(s,m) = u_n(s) + m$, where $u_n(s)$ is positive, monotonic and strictly concave. Note that the specific functional form of $u_n(s)$ is irrelevant, so long as the agent views his utility of consumption function as constant over the year – the 'optimal' plan in each week is to smooth meal point spending in each week of the program, conditional on previous spending "errors" made, until the expiration deadline.

This quasi-linear form of $U_n(\cdot)$ reflects the institutional fact that the universe of items able to be purchased with points is in the program's context, a small subset of the universe of items that the decision-maker is able to purchase with cash.[19] That is, participants may use their cash budget to

[16] This rules out precautionary savings motives arising from any uncertainty in implementing one's own plan.

[17] While standard models often specify utility as a function of consumption rather than spending, due to our imperfect knowledge of when exactly the consumption takes place, as well as the very precise observation of spending which we see as a value of the study, we find it most accurate to model the decision problem with spending directly in the utility function. We also phrased the survey in terms of 'spending' rather than 'eating' or 'consumption'.

[18] Cash may be modeled as either a stock or flow variable, however in this case, due to assumed quasi-linear utility, the cash budget constraint does not affect the dynamic decision problem.

[19] Recall that in addition, any item in the meal plan can also be purchased with cash. However, the only items which

purchase literally anything in the outside world *including* those items sold in the program, whereas they may only use their meal point budget to purchase those items available within the program.

Due to this nesting of available products using the two different payment means, we find it reasonable to assume that the marginal utility of point purchases is decreasing whereas the marginal utility of cash purchases for participants is essentially flat. An intuitive interpretation is that participants generally tire more quickly of meal point purchases than they do of cash purchases. It is this diminishing marginal utility of meal point purchases that makes smoothing of meal point purchases over time desirable, regardless of how much an individual likes or dislikes meal plan purchases. Furthermore, the two types of payment methods are not fungible. Cash may be converted to meal points, but meal points may not be converted back into cash. Additionally, meal points expire at time T while cash never expires. The meal point budget is therefore the binding constraint regardless of any possible cash budget or preference heterogeneity across individual participants.

Our model produces an identical spending program across all individuals who do not anticipate needing to purchase additional meal points, which is the reason for our sample selection discussed in Section 2. Excluding those individuals who have clearly higher meal point demand than endowed in the program, participants have the incentive to spend smoothly as possible across weeks, or face one of two unattractive possibilities: not having enough meal points in future weeks, or having to spend more meal points in a future week than is desirable given the assumption of concave utility.

Sections 3.1 through 3.4 describe the spending rules, which give the level of spending in each week as a function of the remaining meal point balance.

3.1. Smoothing With Updating (SU)

The Smoothing with Updating (henceforth “SU”) rule corresponds to each week t’s solution to the general decision problem stated above. Each week, the participant takes into account the current stock of meal points and cash, and re-solves equation (1) subject to constraints (2) and (3). Note that this means the participant implicitly corrects those spending ‘errors’ he or she made in previous weeks relative to the plans made in previous weeks. The first order condition of the general decision problem, with respect to meal point spending equates marginal utilities of meal point spending in current and future weeks.[20] Since our model does not allow marginal utility to fluctuate over time, the solution at week t (for all current and future weeks τ) is

$$s_{n,t}^{SU} = \frac{W_{n,\tau}}{T-t+1} \qquad (4)$$

or simply dividing the remaining point stock evenly between all future weeks. Note that in this context, the solution is a simple and easily implementable rule of thumb, yet requires attention to one’s meal point balance and how many weeks are currently remaining.

3.2. Personal Bias (PB)

In the Personal Bias model (henceforth “PB”), we consider the possibility that some individuals may not spend according to SU, but instead may systematically under or over-spend relative to SU. We summarize the average deviation from SU in each period as a fraction λ. The purpose of this spending rule is to track systematic deviations from smoothing behavior on an individual basis in a simple, reduced-form manner, without speculating as to the exact psychological mechanism underlying the value of the bias parameter. Thus in week t, a participant’s spending plan (for current and future weeks τ, except T) can be summarized as

meal points can buy are those actually sold within the plan.

[20] Since we assume utility is linear in cash and that the cash and point budget constraints do not interact, cash purchases do not affect the inter-temporal meal point spending plan.

$$s_{n,t}^{PB} = \lambda_n \cdot \frac{W_{n,\tau}}{T - t + 1} \qquad (5)$$

where λ_n is an individual-specific parameter that may take value of either greater than or less than 1. This bias parameter can be interpreted as an individual's 'natural' rate of spending from the prepaid account as a fraction of the SU solution, where $\lambda_n = 1$ corresponds to the SU solution exactly.

However, in the final week of the program T, we assume a PB individual will rationally satisfy the meal point budget constraint regardless of his or her value of λ_n. Thus besides merely not wasting anything in the final week, they never 'correct' their personal bias by switching to SU. We use this criteria in order to err on the side of caution in classifying limited attention, since we would like to see at least two weeks worth of weekly spending in support of smoothing behavior.

3.3. Limited Attention (LA)

Finally, we consider a model of Limited Attention (henceforth "LA") in which some individuals who spend under a PB rule initially, may have done so due to limited attention of the dynamic allocation problem. It could be either that they did not initially pay full attention to their remaining point balance, or the number of weeks remaining in the program, or both.[21]

Suppose that individuals may have a plan to spend according to SU, but due to limited attention, they instead implement a plan which can be approximated by PB. At some subsequent week in the program, they begin devoting a greater amount of attention to those state variables which determine the SU solution, and spending behavior at that time shifts discretely from a PB solution to the SU solution. The limited attention rule can thus be represented as:

$$s_{n,t}^{LA} = \begin{cases} s_{n,\tau}^{PB} \forall \tau \in [1, k_n - 1] \\ s_{n,\tau}^{SU} \forall \tau \in [k_n, T] \end{cases} \qquad (6)$$

where k_n is the individual-specific week at which some external factor such as salience draws the participant's attention to the SU solution.[22] We can think of the probability of switching from PB to SU in any given week t being a function of a salience parameter α, which is homogeneous across individuals for simplicity. That is, $\Pr(k_n = t) \equiv f(\alpha)$, where $\frac{\partial f(\alpha)}{\partial \alpha} > 0$. We can further assume that salience is a function of time, specifically increasing in temporal distance and similarity to the deadline T. That is, $\frac{\partial \alpha}{\partial t} > 0, \forall t$, and $\frac{\partial \alpha}{\partial s(t,T)} > 0$, where $s(t,T)$ represents how closely week t resembles week T, such as both being at the end of an academic quarter.

Based on this framework, we would expect to observe an increasing number of switching weeks as time approaches the expiration deadline, and at weeks resembling and nearby the deadline such as weeks 11 and 22 (end of quarters).

In practice, the adjustment after week k_n could be partial rather than complete. That is, even after the week of starting to pay attention, the participant may only adjust his or her spending rule a

[21] Although our model of behavior resulting from limited attention does not distinguish between whether attention was limited with respect to the budget constraint or with respect to the time horizon, the empirical results indicate that attention devoted to the time horizon was the driving factor.

[22] Suggestions in the literature about external factors determining attention include salience (see Chetty, Looney and Kroft, 2009; Brown, Hossain and Morgan, 2010), and the number of competing stimuli (see DellaVigna and Pollet, 2009). DellaVigna (2007) provides a model of salience and number of competing stimuli determining the consumer's perceived value of an object, and also gives a survey of related empirical evidence.

fraction of the way.[23] Given our limited number of weekly observations for each participant, and the fact that we estimate decision rules on an individual basis, we do not attempt an estimation of this possible rule here. Within the current set of spending rules considered, such individuals would classify as either LA or PB depending on how close their spending behavior is to each.

3.4. Suggested Plan (SP)

The Suggested Plan (henceforth "SP") solution is equivalent to the participant solving the general decision problem in t = 1, but not re-calculating in any subsequent weeks. In other words, the consumer makes a spending plan at t = 1 which is identical to that in SU, however in subsequent weeks the participant *never* revises this original plan in response to ex-post errors. SP suggests a strict adherence to the original spending plan, which is less flexible, less economically intuitive, and less optimizing in nature than SU. SP corresponds to the spending plan recommended by the university shown below:

Based on 53 meal points per week; Meal points expire at the end of Spring quarter, are non-refundable and non-transferable.

Fall quarter		**Winter quarter**		**Spring quarter**	
orientation	1800				
week 1: Sunday, Sept 25:	1747	week 1: Sunday, Jan 8:	1164	week 1: Sunday, April 2:	581
week 2: Sunday, Oct 2:	1694	week 2: Sunday, Jan 15:	1111	week 2: Sunday, April 9:	528
week 3: Sunday, Oct 9:	1641	week 3: Sunday, Jan 22:	1058	week 3: Sunday, April 16:	475
week 4: Sunday, Oct 16:	1588	week 4: Sunday, Jan 29:	1005	week 4: Sunday, April 23:	422
week 5: Sunday, Oct 23:	1535	week 5: Sunday, Feb 5:	952	week 5: Sunday, April 30:	369
week 6: Sunday, Oct 30:	1482	week 6: Sunday, Feb 12:	899	week 6: Sunday, May 7:	316
week 7: Sunday, Nov 6:	1429	week 7: Sunday, Feb 19:	846	week 7: Sunday, May 14:	263
week 8: Sunday, Nov 13:	1376	week 8: Sunday, Feb 26:	793	week 8: Sunday, May 21:	210
week 9: Sunday, Nov 20:	1323	week 9: Sunday, Mar 5:	740	week 9: Sunday, May 28:	157
week 10: Sunday, Nov 27:	1270	week 10: Sunday, Mar 12:	687	week 10: Sunday, June 4:	104
Finals week: Sunday, Dec 4:	1217	Finals week: Sunday, Mar 19:	634	Finals week: Sunday, June 11:	51
end of quarter total	1164	*end of quarter total*	581	*end of quarter total*	0

In the framework of the general decision problem specified above, SP is not fully rational since he or she does not incorporate previous spending errors to reconfigure a new spending plan in *each* subsequent week through the end of the program. By contrast, the SP participant will attempt to follow the exact weekly balance in the above table in each week, even if it means spending a very low or very high amount to 'catch up' in accordance with the budgeting calendar.

Some participants might use the calendar as a type of self-commitment (albeit without an explicit externally imposed penalty for not following it). In this case the calendar could serve as a source of information regarding where they are "supposed to be" in the plan at different times of the year, and participants might judge their own weekly spending performance based on the calendar.

4. Empirical Results

We estimate each of the spending rules in Section 3 for each program participant, using

[23] For example, a partial adjustment (PA) rule might be modeled as

$$s_{n,t}^{PA} = \begin{cases} s_{n,\tau}^{PB} \forall \tau \in [1, k_n - 1] \\ \varphi \cdot s_{n,\tau}^{SU} + (1-\varphi) \cdot s_{n,\tau}^{PB} \forall \tau \in [k_n, T] \end{cases}$$

where α reflects the degree of adjustment to smoothing compared to continuing with the previously used rule. Estimating PA would be difficult in this particular setting due to the fact that we have few observations per individual and the results show most of the switching happening with only very few weeks remaining to estimate α from (modally 2). The introduction of this additional parameter may also take explanatory power away from k_n given our limited observations, since it would allow for a gradual adjustment rather than an abrupt one.

maximum likelihood estimation as follows: The observed data from participants' pre-paid accounts are assumed to follow the process:

$$s_{n,t}^{data} = s_{n,t}^{rule} + \varepsilon_{n,t}^{rule}$$

where *rule* ϵ {SU,PB,LA,SP}. In the absence of a budget constraint, $\varepsilon_{n,t}^{rule} \sim N(0, \sigma_n^{rule2})$, so that each person-solution combination has its own error variance to be estimated. We interpret those errors as being spending "mistakes" that are due to unexpected idiosyncratic factors in a student's life that week. For simplicity we assume that decision-makers are naïve about those errors ex-ante.[24]

With the budget constraint, the actual error distribution used in the estimation will be a truncated normal distribution $\varepsilon_{n,t}^{rule} \sim N(0, \sigma_n^{rule2}, -s_{n,t}^{rule}, W_{n,t} - s_{n,t}^{rule})$ to account for moving endpoints of the error distribution, particularly in the initial and final weeks when the participant is near the resource constraint.[25] The individual log likelihood function is given by the sum of log probability density functions of $\varepsilon_{n,t}^{rule}$ over all time periods observed:

$$\ln L = \sum_{t=1}^{T} \ln \varphi(\varepsilon_{n,t}^{rule})$$

where ϕ is the truncated normal probability density function.[26] The estimation procedure finds the parameter values which maximize the above log likelihood expression given the observed data.[27]

Note that while PB nests SU, neither LA nor SP are parametrically nested with respect to any of the other spending rules. Therefore in order to compare fits we need to use statistical model selection criteria. Due to the importance of allowing for heterogeneity in individual parameter estimates, and the limited observations for each individual, we implement a classification procedure utilizing the Vuong test for non-nested models instead of a mixture model approach which would impose pooling of parameters across individuals. This also allows each spending rule under each participant to have its own error variance parameter.

A summary of the parameters estimated for each of the spending rules is shown in Table 1.

[24] Assuming naivete about the decision-maker's own future spending errors is key for our simplified empirical analysis otherwise participants would need to be making a dynamic plan with uncertainty. Such plans are likely to result in gradual adjustment of spending plans rather than the suddenly adjusting plans we are most interested in.

[25] Goldman (2000) shows that MLE with truncated errors retains asymptotic normality.

[26] This is given by $\dfrac{\left(\dfrac{1}{\sigma_n^{rule}\sqrt{2\pi}}\right) \cdot e^{\frac{-\varepsilon_{n,t}^{rule2}}{2\sigma_n^{rule2}}}}{\psi(-s_{n,t}^{rule}) - \psi(W_{n,t} - s_{n,t}^{rule})}$ where ψ is the cumulative distribution function for $N(0, \sigma_n^{rule\ 2})$.

[27] The limited attention model is estimated similarly, except that we scan individually over possible values of k_n since it can only take on a finite number of integer values and thus creates discontinuities in the likelihood function. In other words, the optimization procedure is $\underset{k_n}{Max}\left\{\underset{(\sigma_n,\lambda_n)}{Max}\{\ln L\}\right\}$ where $k_n \epsilon [2,32]$. Since k_n takes on discrete values, we do not attempt to obtain standard errors for the estimates, but simply take the value of k_n yielding the greatest likelihood.

Table 1: Parameters Estimated for Each Model

	SP (Suggested Plan)	SU (Smoothing with Updating)	PB (Personal Bias)	LA (Limited Attention)
σ_n	Yes	Yes	Yes	Yes
λ_n	No	No (restricted to 1)	Yes	Yes
k_n	No	No	No	Yes

Using the estimation results, we then categorize each account holder by the solution which provides the best fit to their individual spending profile. Since SU is parametrically nested in PB, we can compare the relative fits of those two solutions using likelihood-ratio tests. Since the other models are not nested parametrically, we use the Vuong (1989) test for non-nested models to find the best fit out of the four models, giving the more 'rational' models the benefit of the doubt.

The following sorting algorithm is used to categorize each participant:

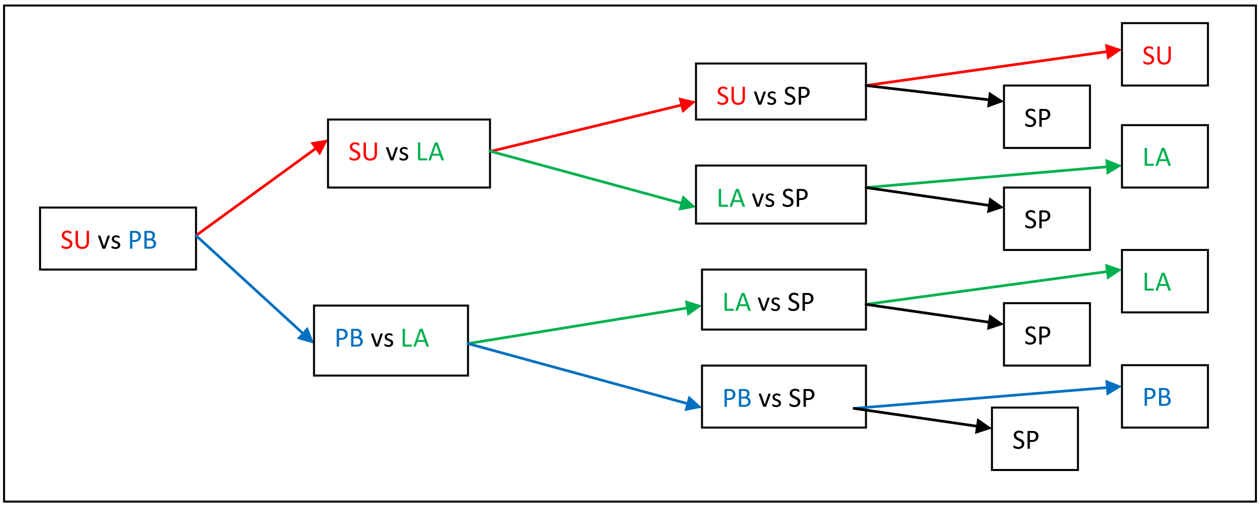
Step 1: For each participant, either reject or fail to reject SU using likelihood ratio test; if reject then temporarily categorize as PB, and if fail to reject, *temporarily categorize* as SU;

Step 2: Using the temporary categorizations in Step 1, compare current categorization with LA using Vuong test. In the case that the Vuong test is unable to accept or reject either model, categorize the participant as the more 'rational' of the two models (in other words, categorize as LA over PB and SU over LA);

Step 3: Using the categorizations of Step 2, which will have sorted individuals temporarily into one of {SU, LA, PB}, compare to SP using the Vuong test.[28]

An illustration of the sorting procedure is shown in Figure 4.

Figure 4: Sorting Participants



The sorting results are displayed in Table 2. Approximately half of account holders appear to be spending as though they are updating their plans on a weekly basis without significant bias. The

[28] Note that SP is typically overwhelmingly rejected in favor of any other model since it suggests that each week participants will always correct previous errors retroactively, rather than re-optimizing over the remaining weeks. Subjects appear to have a stronger economic intuition than the suggested plan. This is in fact encouraging for our assessment of individuals' natural optimizing tendencies.

remaining half of account holders are spending with a statistically significant personal bias, with about one-third of total participants having a significant regime switch in their spending pattern at some week in the middle of the program.[29]

Table 2: Sorting Results, Percentage of Sample

	90% level*	***95% level****
Suggested Plan (SP)	0%	0%
Smoothing with Updating (SU)	46.4%	47.7%
Personal Bias (PB)	20.6%	20.5%
Limited Attention (LA)	33.0%	31.8%

**denotes significance level of Vuong tests. Likelihood ratio tests at 95% confidence interval in both columns.*

The meaning of an individual being statistically classified as following the Limited Attention solution is quite specific. Being classified as LA compared to SU means that the change in spending pattern in week k_n cannot be simply dismissed as noisy spending under the SU rule. It is also not statistically better described as a general spending trend implied by PB. In other words, the spending pattern is not just noise around the optimal solution without bias, nor is it accounted for as part of a continuous trend in spending to satisfy the point budget constraint. Rather, it is a discrete shift in behavior from one pattern to another, where the second pattern is significantly better explained by SU than PB.

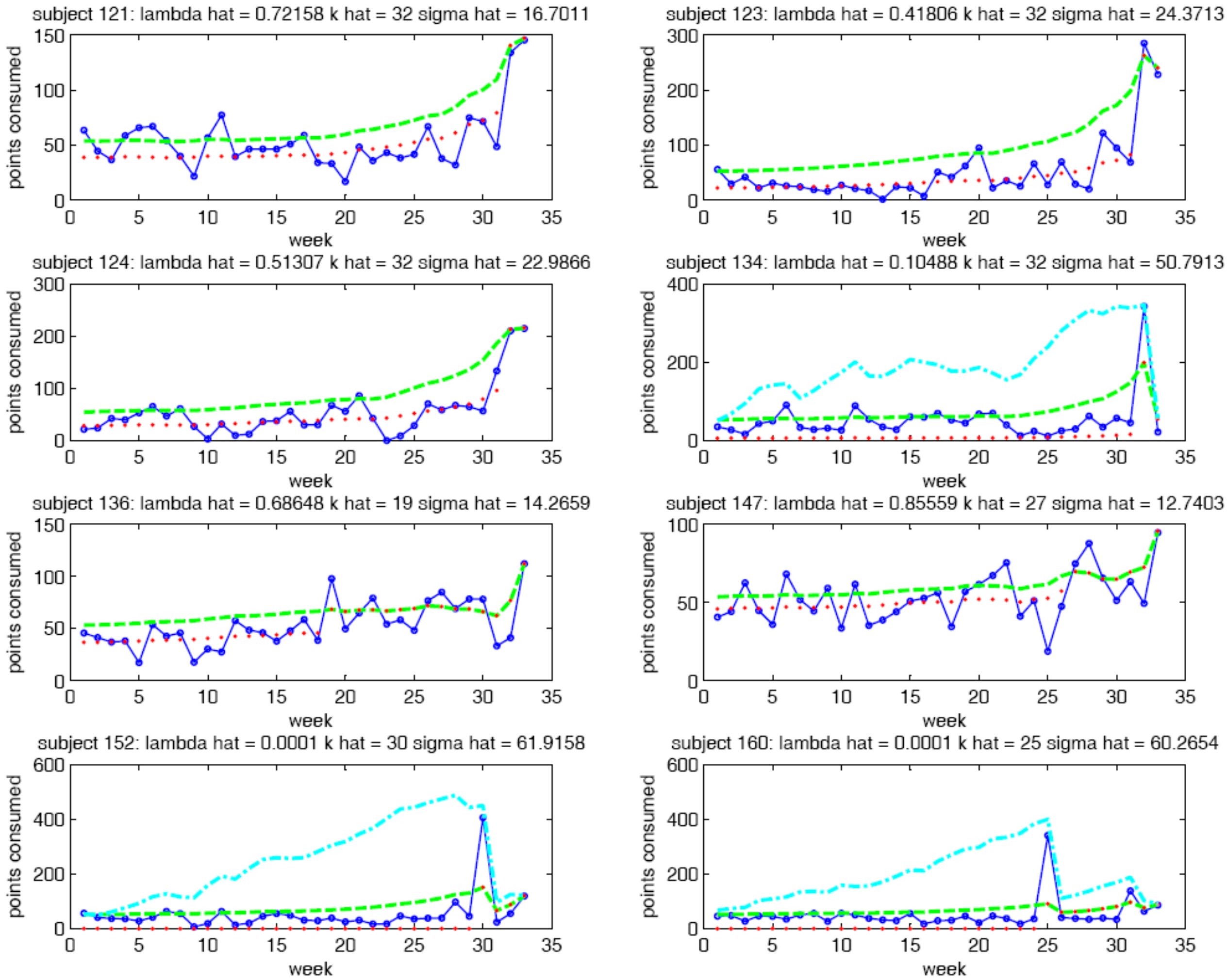
The next section and Appendix C show sample spending profiles from each group. The differences between LA and PB are best seen by comparing the profiles of each type from Appendix C, where participants' spending efforts in the Limited Attention case are often visually clear. The estimated distributions of personal bias parameters λ are shown in Appendix E, omitted here because the distribution of bias parameters is tangential to our focus on attention.

5. Limited Attention Participants

We now turn to the Limited Attention participants in detail, discussing their ability to account for the program-wide spending increase. Figure 5 shows examples of participants classified as Limited Attention spenders under the previously described sorting algorithm. Examples of the other two estimated spending types are shown in Appendix C.

[29] Aggregating the data by week creates a lower bound estimate of the number of participants who might be instantaneously switching to the SU solution, since some people may switch mid-week in the final week of the program.

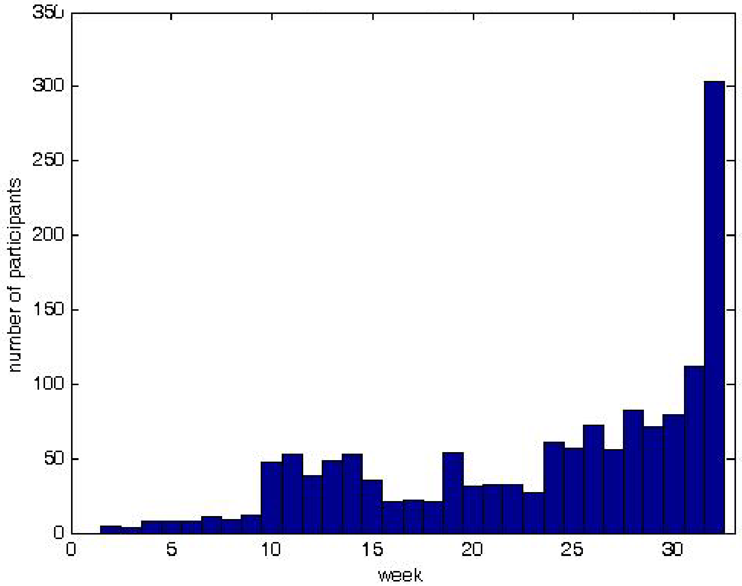
Figure 5: Examples of Limited Attention Participants' Spending Profiles



Examples of individuals categorized as following Limited Attention (LA) rule: Dark blue: actual spending data; Red: sorted rule (Limited Attention, LA); Green: Smoothing with Updating (SU) rule; Light blue: Suggested Plan (SP) Note: SP not included in charts where difference is too large to scale properly.

Figure 6 shows the distribution of estimated regime-switching weeks among the 1474 individuals statistically classified into LA. The distribution of switching weeks corresponds quite closely to the increases in retail sales volume initially shown in Figure 2, and also corresponds to our hypothesis about when a limited attention individual should have high likelihood of attention, described in Section 3.3.

Figure 6: Limited Attention Participants, Estimated Week of Switch to SU, N = 1474



First, the histogram shows that the conditional probability of switching to the SU solution is increasing in proximity to the week 33 deadline. Furthermore the proportion of individuals switching into the SU solution is overwhelmingly the highest in week 32, the week immediately prior to the expiration deadline. Finally, the conditional likelihood of switching increases substantially after the first third of the program (corresponding to the end of the 1st academic quarter). This is consistent with our limited attention framework in that even though points do not expire at the end of the each quarter, the actual expiration deadline becomes more psychologically salient at that time.[30]

Such a psychological salience effect does not seem as dramatic at the end of the second quarter, but appears to have an increasing impact in the weeks before expiration, when the deadline is most salient. Although there is a small increase in volume of consumers switching at week 19, the increase is not as substantial and persistent as the increase in switching occurring at week 10. We can think of two possible reasons for this: First is the fact that the holiday break (spring break) following the 2nd quarter is substantially shorter than that following the 1st quarter (winter break) – participants may view the spring holiday as less of a true break than the winter holiday, leading to lower likelihood of increased attention. Another possibility is selection – those with tendencies to begin paying attention early already did it right after week 10, while the remaining Limited Attention participants simply responded to the expiration deadline itself.

How much of the aggregate retail activity in Figure 1 do Limited Attention participants account for? Figure 7 shows that although Limited Attention participants comprise just 30% of participants in the sample (and no more than 25% of all participants when one incorporates the participants dropped in the sample selection), they made up a steadily increasing proportion of retail sales purchases as the deadline neared – comprising almost 90% of all retail sales by week 32.[31]

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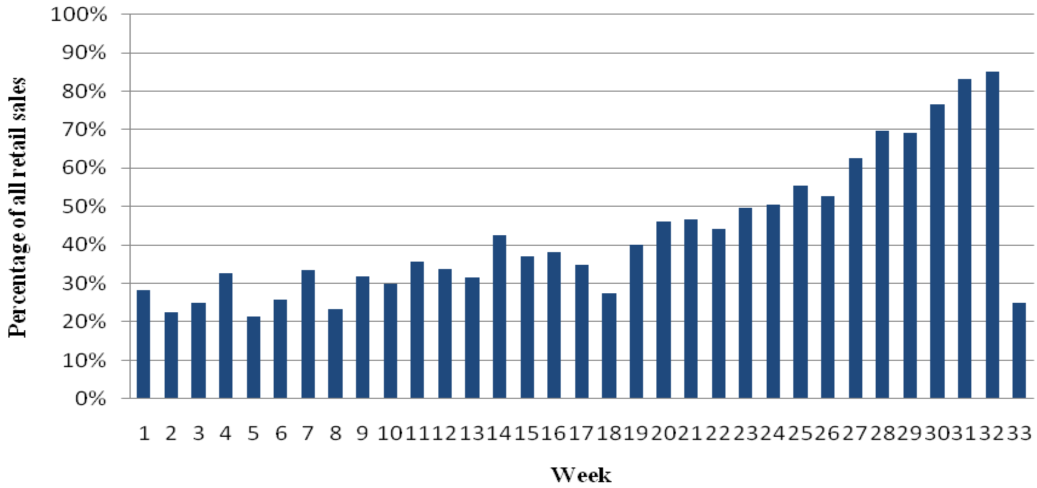
[30] An analogy might be individuals who start preparing their taxes on March 15th, a month ahead of the actual April 15th tax deadline since the calendar date 15 serves as a reminder.

[31] Note that the sudden drop in week 33 is due to the fact that PB account holders often made large retail purchases in week 33, and can arguably be considered LA with switching to SU in week 33. However, we do not categorize those individuals as having limited attention since given our weekly aggregation of the data, their spending choice in week 33 is confounded with merely satisfying the meal point budget constraint.

Figure 7: Limited Attention Share of Retail Sales



6. Possible Alternative Explanations and Survey Evidence

In this section we address potential alternative explanations for the spending patterns observed for individual participants: intentional delay, uncertainty, and negative time preference. We supplement the data analysis presented so far with survey evidence which addresses the above alternative explanations.

The survey was conducted in an Introductory and Intermediate Economics course with 100% response rate from those enrolled in the plan. It was conducted in week 32 of the 2007-2008 plan which was *identical* to the plan empirically analyzed except that the number of points per participant was 2100 rather than 1800. Since the survey was conducted in a different program year than the data analyzed, the survey responses cannot be matched to any actual spending data. The primary purpose of the survey was to better understand how participants approached spending decisions in the meal plan.

Participants were asked how they had planned to use their meal points, how they actually used them, whether they faced budget uncertainty, whether they faced parental monitoring, and how they adjusted their spending when they found themselves ahead of or behind their desired spending schedule. The detailed survey results are shown in Appendix D, including disaggregation of spending plan responses by demographic characteristics, including gender, major, and previous experience in the plan.

6.1 Intentional delayed spending for durable purchases

One possibility is that participants who spent substantial amounts in the final weeks of the program fully anticipated and intended doing so. However, 90% of survey respondents reported an intended use *other* than spending more later in the year (see Table 1s in Appendix D). In addition, it would be highly coincidental that estimated limited attention participants who increased their spending later in the year also just so happened to do so in a way which was more consistent with smoothing than with personal bias plus noise.

In fact, in the actual spending data, many limited attention participants hit the smoothing solution *almost exactly* in the final two weeks of the program, dividing remaining expenditures almost precisely evenly between the final two weeks. It is highly unlikely that such individuals would intend to spend in such a way in the beginning of the program. Rather, it is more plausible that the smoothing motive was realized late in the program as a response to the expiration deadline.

In addition since the retail purchases are generally of a more durable nature than other program purchases by design of the program, there is actually a motive to make such purchases *earlier* in the year rather than later in the year, if participants know their demand for meal purchases is low. Participants can then have more opportunities to consume and utilize those retail items over the course of the year, rather than only in the final week of the program before leaving campus. This argument holds for pre-packaged foods, as well as for more durable equipment such as kitchen and dormitory appliances purchased.

Finally, in the comments in the survey, some respondents actually mentioned wanting to avoid spending on durable goods from the campus store, as those items were seen as overpriced.

6.2 Uncertainty

One possible explanation for not following the smoothing with updating solution is that there is a significant source of uncertainty in this field context that has not been properly accounted for in the model. Although we have argued that compared to other dynamic planning problems, the spending decision considered here is essentially devoid of time horizon and price uncertainty, there are still some plausible sources of uncertainty in the decision problem.

Uncertainty in either the cash or points budget constraint is one of these plausible sources. We attempted to reduce this possibility by censoring the sample to remove those participants who had to consider whether to deposit more money into their accounts. In a survey of 81 plan participants, we asked whether participants were personally "uncertain about whether (they) could actually afford to buy more meal points if (they) needed them".

Very few survey respondents reported substantial budget uncertainty, with just 6 participants reporting 'quite a bit' or 'extreme' concern about being able to afford additional points (See Table 5s in Appendix D). Additionally, when cross-tabulated with the responses to the question of how they intended to use the meal points, those who had more budget uncertainty were actually *more likely* to state an intention to use points evenly over the year. This is intuitive, since deviations from the SU solution are likely to have a higher utility loss for those who have lower cash resources available to them. Thus budgetary uncertainty is an unlikely source of the drastic sales growth nearing the expiration deadline.

6.3 Time preference anomalies

Another possibility is that negative time discounting is a cause of higher expenditures later in the year compared to earlier in the year. The literature on time preference generally has not found definitive evidence for negative time preference (see Frederick, Loewenstein and O'Donoghue, 2002 for a survey). However, since the aggregate time trend of spending in our data is upward sloping, it is worth considering this as a potential alternative explanation for behavior.

Simple negative time preference predicts that at any point in time they are asked, individuals should state a preference for spending *less now and more later*. However, in the survey of plan participants, only 10% of respondents stated a preference for using more points later in the year (Table 1s, Appendix D). The number of respondents reporting wanting to use more points earlier in the year was even fewer (1%), suggesting that time discounting was not a main driving force behind spending behavior in this context.

Furthermore, even if discounting played a role in individual decisions, the negative discount rate would have to be implausibly high and time inconsistent in order to account for the extreme week-on-week growth in expenditures seen in many individual profiles (see Section 5 and Appendix C for examples). A similar argument holds for the idea of relative 'dislike' of purchasing items with meal points as compared to outside items (in the spirit of O'Donoghue and Rabin, 1999). While an increasing profile of within-plan spending might be explained by such a model, the very non-gradual nature of significant spending rule changes indicates that this was not the main source of observed behavior.[32]

6.4 Survey evidence for limited attention

Finally, we consider whether there is any direct support for the limited attention hypothesis in the survey evidence. One possible indication of limited attention from the survey is that 44% of respondents answered “Which of the following best describes how you intended to use your meal points?” with the answer “as necessary” as opposed to the other more specific options (Table 1s, Appendix D). Compared to the other possible responses to this question, “as necessary” might be suggestive a type of viscerally motivated spending that is not particularly concerned with the dynamic planning aspect of the program or concern about the expiration of points.[33] The adjustment detected in the program strongly suggests that participants do in fact want to smooth their spending – but it is frequently a matter of when they arrive at this realization. This realization was empirically most likely to occur near the expiration deadline (weeks 31 and 32), and for some people, during a time period (week 10) which resembled the future expiration deadline.

A comparison of the distribution of responses about meal point use intentions, and the corresponding question of how respondents *actually* used their meal points, shows that spreading point use evenly was more prevalent in intended use (42%) than occurred in practice (17%).

7. Discussion and Conclusions

We empirically examine spending patterns in a residential program context which is simpler than most dynamic spending tasks in the field due to several key features: the horizon of the planning problem is clear, price fluctuations are essentially non-existent, and transactions costs of spending are extremely low due to convenience and geographic proximity of facilities. We reconcile two pieces of empirical evidence: First, the fact that participants demonstrated the desire to smooth their spending over the year (as evidenced both by survey responses, and statistical fits to spending rules incorporating eventual adjustment as characterized by smoothing); Second, the fact that half of participants are spending in a manner clearly different from smoothing.

The explanation the paper offers is that indeed, participants want to smooth their spending a priori – but doing so requires paying attention on a weekly basis to how many weeks they have left in the program and how many meal points they have left. Minding these factors on a daily or even on a weekly basis is cognitively costly, as is much of financial planning in real life – and so participants tend to not pay attention to it until it becomes urgent to do so. Estimating *when* exactly those individuals begin paying attention, it in fact tends to happen quite close to the expiration date (and dates which are similar to it). This is in line with findings using survey data that most young people do not begin planning for future life events until quite a few years after they are capable of starting to do so (Madrian and Shea, 2001). This paper suggests that such late planning behaviors may be driven at least in part by a lack of salient reminders that switch an individuals’ planning mode ‘on’. This is encouraging news about individuals’ planning capabilities, in that it suggests that deadlines, for at least some people, serve as an effective psychological push towards implementing a plan.

Our empirical conclusions were drawn by estimating four simple spending rules which varied in their adherence to notion of spending smoothly. First, we considered the possibility that individuals

[32] Hyperbolic discounting models also tend to predict smoother dynamic consumption paths than those observed in this data. For examples, see Laibson (1997), Shapiro (2005), Angeletos et al (2001), Stephens (2003), and Mastrobuoni and Weinberg (2009).

[33] See Brown, Chua and Camerer (2009) for an experimental examination of dynamic consumption saving behavior with a ‘visceral’ thirst condition.

approximately smooth their spending by taking the current balance of meal points and dividing evenly by the time period remaining in the program, in order to determine how much to spend in the current week. Next, we considered the possibility that individuals systematically under-spend or over-spend relative to the aforementioned rule, and continue to do so throughout the entire time horizon of the program. Third, we considered the idea that individuals may begin by systematically under or over-spending relative to the complete smoothing rule, but that at some point in time they switch spending rules to complete smoothing. The time of switching was estimated as a structural break in individual-level spending patterns, and the statistical significance of the structural break was tested by using statistical model selection criteria to assess the fits with the regime switch in the model and without it. Finally, the fourth spending rule was the one recommended by the residential program itself. Due to the importance of estimating parameters on an individual-level to allow for initial spending rule heterogeneity, a sorting procedure utilizing Vuong and likelihood ratio tests was used to classify each participant.

Three main empirical facts should be taken from the results: First, spending smoothly was in fact an intention of program participants, evident from participants' survey responses as well as the estimation results. Second, a substantial proportion of individuals were best explained by a spending rule with regime switching towards the smoothing model. The distribution of switching weeks is consistent with the prediction of limited attention models, with time salience of the expiration deadline inducing attention to the dynamic planning task. A final point is that these limited attention individuals have a significant "macro-level" impact on overall total spending activity occurring in the program.

Using this data alone, we are unable to trace the exact external source which prompted increased attention in the program. That is we do not know the exact mechanism through which the deadline influenced individual spending decisions. For example, were participants most effectively influenced by reminders posted in the dining halls, through peer effects, or other factors? While addressing this issue is policy relevant in its potential application to other dynamic spending and savings settings, we leave more rigorous exploration of this question and possible policy applications to future research.

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Appendix A: Sample list of retail items offered

convenience store:

Yoplait yogurt	Betty Crocker fudge brownie mix	Bounty paper towels
Naked juice	Aunt Jemima pancake mix	Ultra Downy
Oscar Meyer deli meats	Hershey's chocolate syrup	Glad storage zipper bags
20 fl-oz soda bottles (various)	Skippy peanut butter	Lysol
Campbell's Soup at Hand	Pepperidge Farm Goldfish	Softsoap
Easy Mac	Wheat Thins (low sodium, multigrain, ranch)	Bic razors
Poptarts	Loaf of bread	Stainless steel silverware
Honey Nut Cheerios	Kashi TLC cookies	Scotch tape
Ben and Jerry's ice cream (various)	Oreo	Shout stain remover
Cup of Noodles	Spam	Colgate toothpaste (various)
Cheez-Its (various)	Doritos	Listerine
Arizona Tea	Apple Chips	Tide detergent
Milk	Hunt's snack pack pudding	Kleenex boxes
Progresso Soup	DeCecco pasta	Paper plates and cups
Eggs	Prego pasta sauce	Alba botanica shampoo and conditioner
Tropicana orange juice, 64 fl-oz	Ritz crackers	Bicycle playing cards

online store:

Batteries Duracell AA	Shampoo Pantene	
Tylenol Extra Strength Gelcaps	Razor Blades Gillette Mach 3	Arrowhead Mountain Spring Water
Lotion Vaseline Intensive Care	Dental Floss Glide	Diet Coke
Soap Bar Irish Spring	Snickers Candy Bars	Rice Calrose White
Clorox Disinfectant Wipes	Red Bull Energy Drinks	Paper Hewlett-Packard Printer
Power Bar Variety	Starbucks Variety Frappuccinos	Notebooks
Post-it Notes	Martinellis Apple Juice	

Appendix B: Meal summary statistics

Meals eaten within the program were tabulated using the following criteria: All transactions in the program are one of four possible types: breakfast, lunch, dinner or retail. All meals are defined as purchases made at a sit-down dining facility (ie. not at the campus store or online). Breakfast is defined as any such purchase made between 2:00AM and 10:59AM. Lunch is any such purchase made between 11:00AM and 4:59PM. Finally, Dinner is any such purchase occurring between 5:00PM and 1:59AM. Note that most dining facilities close late at night and are not 24 hours. While the time cutoffs are made somewhat arbitrarily, our aim is to have an idea of how often participants eat meals within the plan, and how much they spend.

Figure B1: Average expenditure per meal consumed, by participant

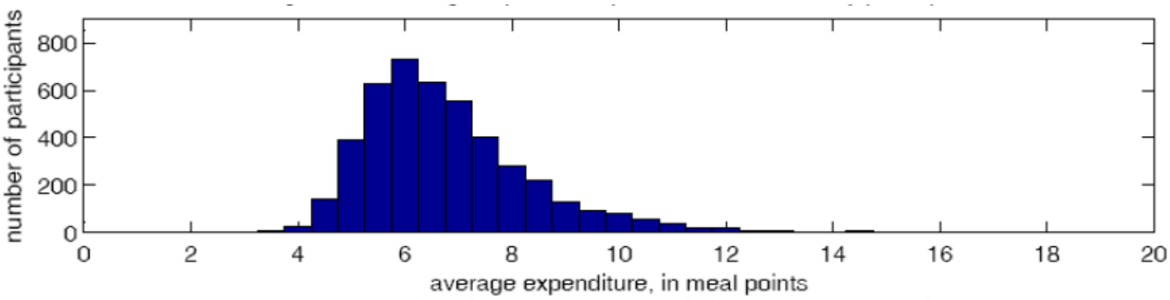


Figure B2: Average proportion of meals consumed within meal plan, by participant

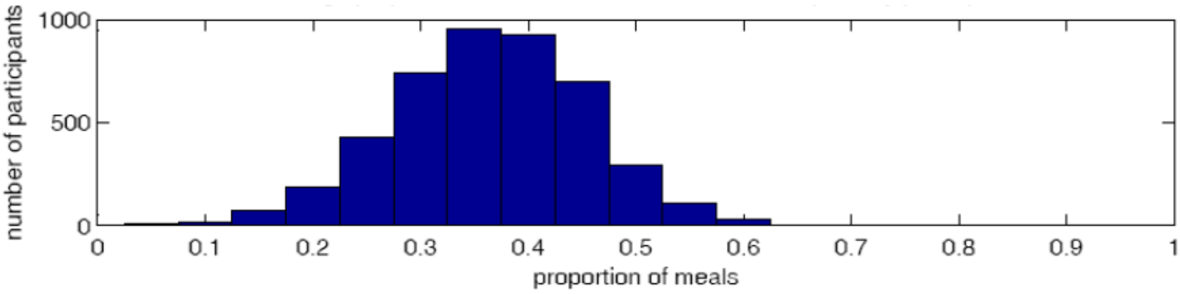
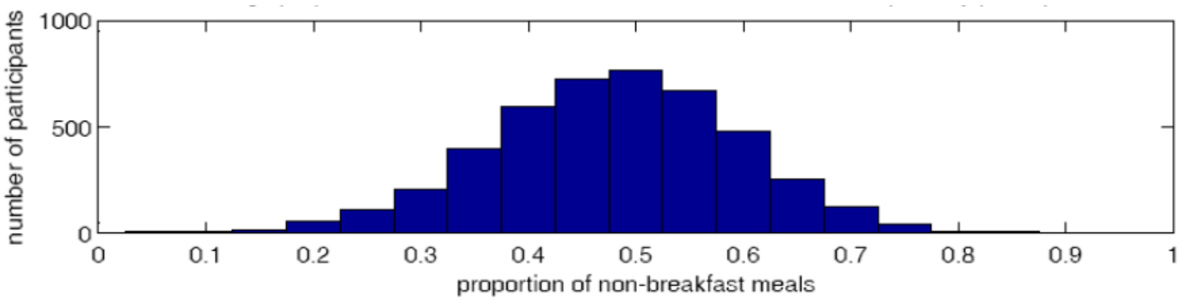


Figure B3: Average proportion of non-breakfast meals consumed within meal plan, by participant



Appendix C: Example Spending Profiles

Figure C1: Smoothing with Updating (SU)

Sample of individuals categorized following Smoothing with Updating (SU) rule: Dark blue: actual spending data; Red: sorted rule (Smoothing with Updating; SU); Light blue: Suggested Plan (SP)

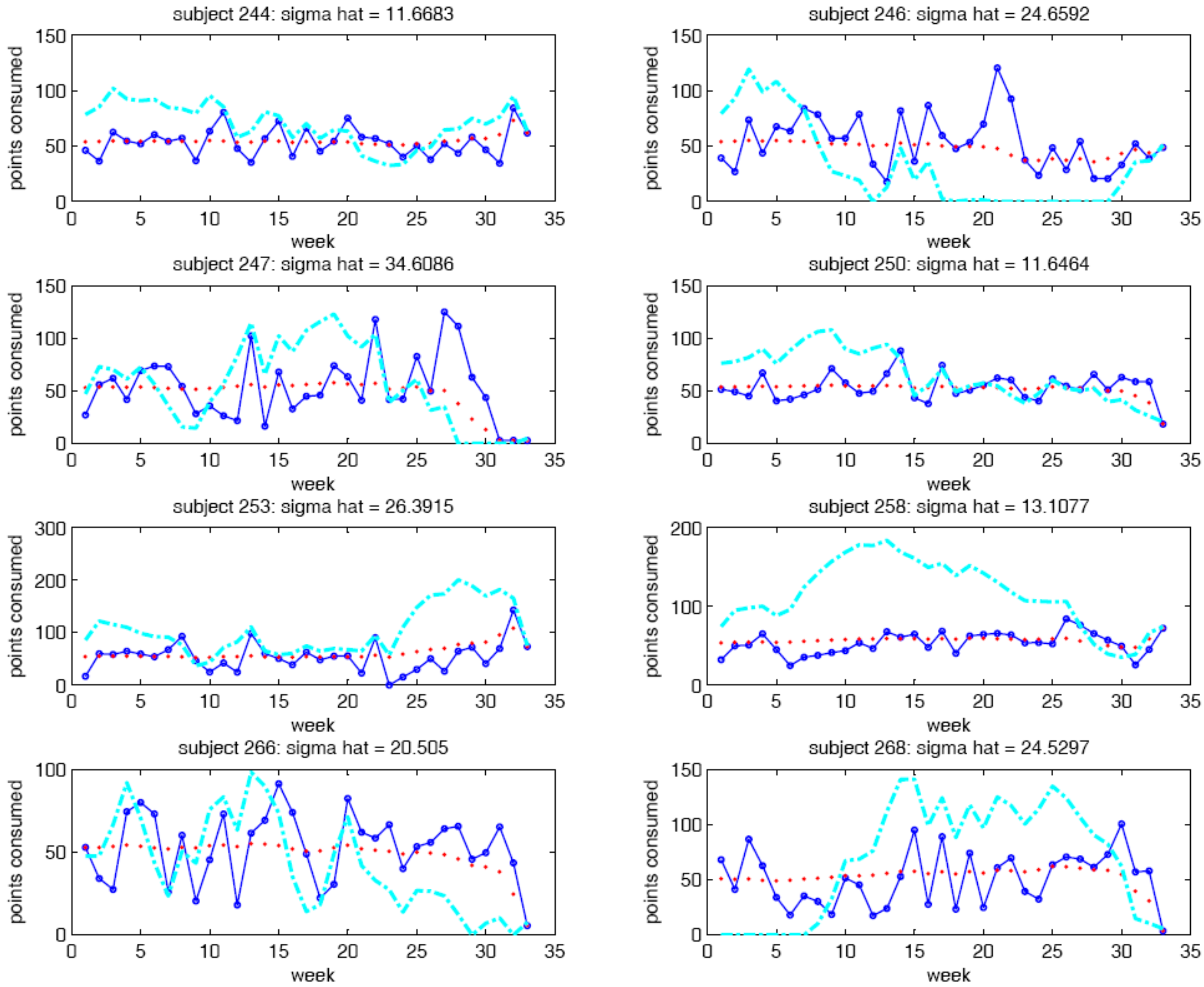
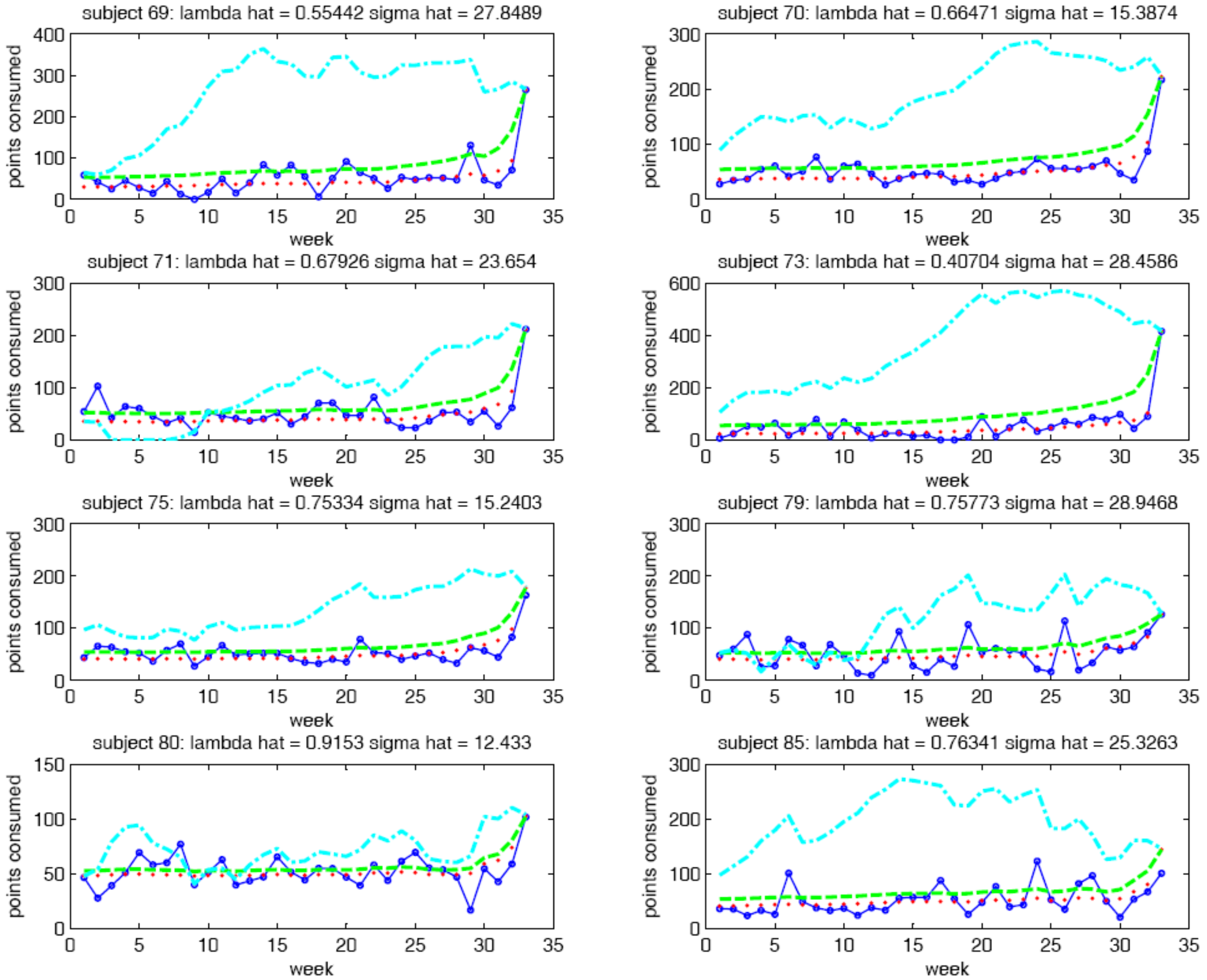


Figure C2: Personal Bias (PB)

Sample of individuals categorized following Personal Bias (PB) rule: Dark blue: actual spending data; Red: sorted rule (Personal Bias, PB); Green: Smoothing with Updating (SU) rule; Light blue: Suggested Plan (SP)



Appendix D: Residential Program Participant Survey

The survey was conducted in an Introductory and Intermediate Economics course with 100% response rate from those enrolled in the plan. It was conducted in week 32 of the 2007-2008 plan which was identical to the plan empirically analyzed except that the number of points in the plan per participant was 2100 rather than 1800. Since the survey was conducted in a different year than the data analyzed, we are not able to match the survey responses to any actual spending data. Instead, we use responses to assess whether certain participant characteristics are associated with different reported spending intentions and outcomes.

Figure D1: Most frequently visited facility to use meal points, by participant

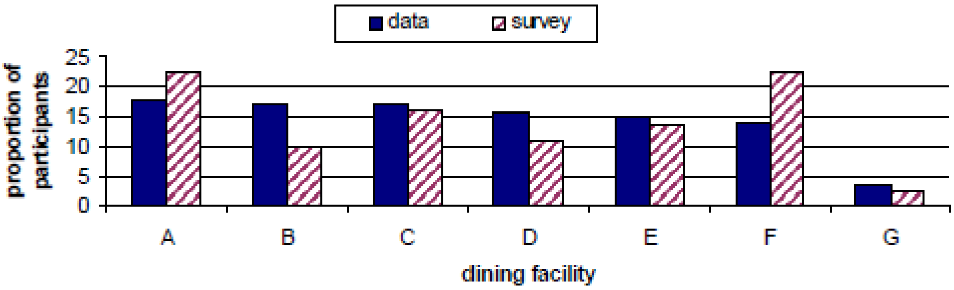


Table D1:	***Which of the following best describes how you intended to use your meal points?***						
	spread evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	*N*
% of all males	40.0%	2.2%	8.9%	0.0%	44.4%	4.4%	
	18	*1*	*4*	*0*	*20*	*2*	*45*
% of all females	44.4%	0.0%	11.1%	0.0%	44.4%	0.0%	
	16	*0*	*4*	*0*	*16*	*0*	*36*
% of total	**42.0%**	**1.2%**	**9.9%**	**0.0%**	**44.4%**	**2.5%**	
	34	*1*	*8*	*0*	*36*	*2*	
	Which of the following best describes how you actually used your meal points?						
	spread about evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	
% of all males	22.2%	13.3%	13.3%	6.7%	37.8%	6.7%	
	10	*6*	*6*	*3*	*17*	*3*	*45*
% of all females	11.1%	8.3%	19.4%	5.6%	52.8%	2.8%	
	4	*3*	*7*	*2*	*19*	*1*	*36*
% of total	**17.3%**	**11.1%**	**16.0%**	**6.2%**	**44.4%**	**4.9%**	
	14	*9*	*13*	*5*	*36*	*4*	
N = 81							

Table D2: ***QA: I was uncertain about whether I could actually afford to buy more meal points if I needed them***

	not at all	a little	somewhat	quite a bit	extremely	this did not apply to me	
% of total	**40.7%**	**9.9%**	**11.1%**	**3.7%**	**3.7%**	**30.9%**	
	33	*8*	*9*	*3*	*3*	*25*	

Which of the following best describes how you intended to use your meal points?

reply to QA:	spread evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	*N*
"not at all" or "this did not apply to me"	**37.9%**	**1.7%**	**13.8%**	**0.0%**	**43.1%**	**3.4%**	
	22	*1*	*8*	*0*	*25*	*2*	*58*
"a little" or "somewhat"	**41.2%**	**0.0%**	**0.0%**	**0.0%**	**58.8%**	**0.0%**	
	7	*0*	*0*	*0*	*10*	*0*	*17*
"quite a bit" or "extremely"	**83.3%**	**0.0%**	**0.0%**	**0.0%**	**16.7%**	**0.0%**	
	5	*0*	*0*	*0*	*1*	*0*	*6*

Which of the following best describes how you actually used your meal points?

reply to QA:	spread evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	*N*
"not at all" or "this did not apply to me"	**17.2%**	**8.6%**	**19.0%**	**5.2%**	**43.1%**	**6.9%**	
	10	*5*	*11*	*3*	*25*	*4*	*58*
"a little" or "somewhat"	**17.6%**	**5.9%**	**11.8%**	**5.9%**	**58.8%**	**0.0%**	
	3	*1*	*2*	*1*	*10*	*0*	*17*
"quite a bit" or "extremely"	**16.7%**	**50.0%**	**0.0%**	**16.7%**	**16.7%**	**0.0%**	
	1	*3*	*0*	*1*	*1*	*0*	*6*

N = 81

Table D3: ***Which of the following best describes how you intended to use your meal points?***

	spread evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	*N*
% of all science majors	**39.1%**	**0.0%**	**17.4%**	**0.0%**	**43.5%**	**0.0%**	
	9	*0*	*4*	*0*	*10*	*0*	*23*
% of all economics majors	**41.2%**	**0.0%**	**8.8%**	**0.0%**	**44.1%**	**5.9%**	
	14	*0*	*3*	*0*	*15*	*2*	*34*
% of all other majors	**45.8%**	**4.2%**	**4.2%**	**0.0%**	**45.8%**	**0.0%**	
	11	*1*	*1*	*0*	*11*	*0*	*24*

Which of the following best describes how you actually used your meal points?

	spread about evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	
% of all science majors	**13.0%**	**4.3%**	**21.7%**	**8.7%**	**47.8%**	**4.3%**	
	3	*1*	*5*	*2*	*11*	*1*	*23*
% of all economics majors	**17.6%**	**11.8%**	**14.7%**	**5.9%**	**41.2%**	**8.8%**	
	6	*4*	*5*	*2*	*14*	*3*	*34*
% of all other majors	**20.8%**	**16.7%**	**12.5%**	**4.2%**	**45.8%**	**0.0%**	
	5	*4*	*3*	*1*	*11*	*0*	*24*
N = 81							

Table D4: ***Which of the following best describes how you intended to use your meal points?***

	spread evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	*N*
first year on meal plan	**52.6%**	**0.0%**	**10.5%**	**0.0%**	**34.2%**	**2.6%**	
	20	*0*	*4*	*0*	*13*	*1*	*38*
second (or more) year on meal plan or had meal plan in a previous year	**33.3%**	**2.4%**	**9.5%**	**0.0%**	**52.4%**	**2.4%**	
	14	*1*	*4*	*0*	*22*	*1*	*42*

Which of the following best describes how you actually used your meal points?

	spread about evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	
first year on meal plan	**23.7%**	**5.3%**	**18.4%**	**7.9%**	**39.5%**	**5.3%**	
	9	*2*	*7*	*3*	*15*	*2*	*38*
second (or more) year on meal plan or had meal plan in a previous year	**11.9%**	**16.7%**	**14.3%**	**4.8%**	**47.6%**	**4.8%**	
	5	*7*	*6*	*2*	*20*	*2*	*42*
N = 80							

Table D5:

I thought that my parent/guardian would use knowledge of my meal point usage to help decide how much spending money to give me (reply)	*Which of the following best describes how you intended to use your meal points?*						
	spread about evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	*N*
"not at all" or "this did not apply to me"	**38.7%**	**1.6%**	**11.3%**	**0.0%**	**45.2%**	**3.2%**	
	24	*1*	*7*	*0*	*28*	*2*	*62*
"a little" or "somewhat"	**53.8%**	**0.0%**	**7.7%**	**0.0%**	**38.5%**	**0.0%**	
	7	*0*	*1*	*0*	*5*	*0*	*13*
"quite a bit" or "extremely"	**50.0%**	**0.0%**	**0.0%**	**0.0%**	**50.0%**	**0.0%**	
	3	*0*	*0*	*0*	*3*	*0*	*6*

I thought that my parent/guardian would use knowledge of my meal point usage to help decide how much spending money to give me (reply)	*Which of the following best describes how you actually used your meal points?*						
	spread about evenly	more earlier in the year	more later in the year	more in the middle	as necessary	none of the above	*N*
"not at all" or "this did not apply to me"	**17.7%**	**3.2%**	**21.0%**	**3.2%**	**50.0%**	**4.8%**	
	11	*2*	*13*	*2*	*31*	*3*	*62*
"a little" or "somewhat"	**23.1%**	**15.4%**	**0.0%**	**23.1%**	**30.8%**	**7.7%**	
	3	*2*	*0*	*3*	*4*	*1*	*13*
"quite a bit" or "extremely"	**0.0%**	**83.3%**	**0.0%**	**0.0%**	**16.7%**	**0.0%**	
	0	*5*	*0*	*0*	*1*	*0*	*6*

N = 81

Table D6:	***If at any point I realized I had more meal points left than I had desired, I responded by***			
	buying more expensive meals	buying more pre-packaged goods	eating more often in the dining halls	other
% of those who did not check "I never found myself in this situation"	**40.3%**	**38.7%**	**35.5%**	**25.8%**
	25	*24*	*22*	*16*
N = 62				
	If at any point I realized I had fewer meal points left than I had desired, I responded by			
	buying less expensive meals	buying fewer pre-packaged goods	eating less often in the dining halls	other
% of those who did not check "I never found myself in this situation"	**46.3%**	**11.9%**	**53.7%**	**26.9%**
	31	*8*	*36*	*18*
N = 67				

Appendix E: Personal Bias Parameter Distributions

Figures E1 and E2 show the conditional distributions of personal bias parameters among Personal Bias (E1) and Limited Attention (E2) spenders in our sample prior to their switch. These distributions are shown for informational purposes and should not be interpreted as being representative of the population of meal plan participants, due to the sample selection procedure in which participants finishing their meal points early were dropped.

Figure E1: Personal Bias Account Holders, Personal Bias parameters, N = 922

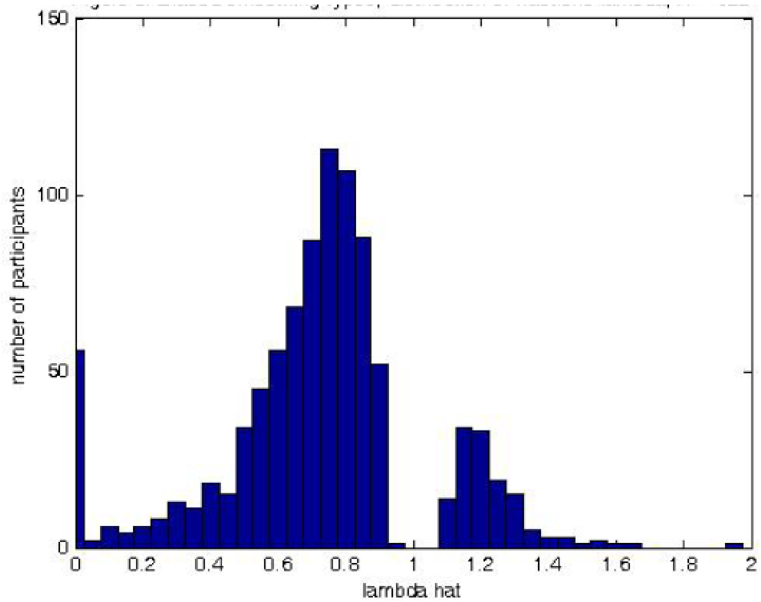


Figure E2: Limited Attention Account Holders, Personal Bias Prior to Switch, N = 1474