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Abstract

We consider a consumption model that takes into account the valuation and demand uncertainties that consumers face while using access services. Typical examples of such services include telecommunication services, extended warranties for consumer electronics, and club memberships. We demonstrate that consumption is affected by contract structure (pay-peruse vs. three part tariffs) even if the optimal consumption plans are identical. We find that a majority of individuals correctly use a threshold policy that is similar to a nearly optimal heuristic, however they use the free units too quickly leading to overconsumption and lost surplus. These errors are partially driven by mistaken beliefs about the value distribution. We also measure subjects' willingness to pay for a contract with free access units, and we find that nearly half of subjects are willing to pay at least the full per-unit price, with a substantial fraction willing to overpay. The optimal firm strategy is therefore to offer a contract that presells access units at a very small discount; this strategy increases revenue by 8 − 15% compared to only offering a pay-per-use contract.

JEL-Code: C910, D030, D120, L110.

Keywords: access services, pricing contracts, decision biases, experiment.

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1 Introduction

Nonlinear pricing of access (subscription) services such as telecommunication, car leasing, club memberships, and product warranties has received a great deal of attention from both researchers and practitioners. Research up to date studies how firms should structure the tariffs (pay-per-use, two part tariff, three part tariff, and unlimited usage) and examines the drivers of consumer's tariff choice. Wilson (1993) reviews the literature on profit- and welfare-maximizing tariff structures. The fundamental assumptions of much of this literature are that consumers are rational decision makers who choose the surplus maximizing tariff and the pricing structure does not influence consumer's value for the service. However, recent studies (Thomas and Morwitz 2005, Soman 2001) show that pricing structures themselves may affect the usage decisions. Indeed, Bertini and Wathieu (2008) state that pricing can transform, as well as capture, the utility of an offer.

The interaction effect between the tariff structure and usage is documented by recent research on telecommunication services (Ascarza, Lambrecht and Vilcassim 2009) and health clubs (Della Vigna and Malmendier 2006). These studies show that consumers do not necessarily choose the tariff that leads to the lowest billing rate for a given amount of consumption. Ascarza et al. find significant differences in total consumption by consumers who choose a two-part and a three part tariff contract which cannot be explained by a change in the budget constraint. In a different context, Iyengar, Jedidi, Essegaier and Danaher (2010) find that consumers have lower utility for two part tariffs compared to pay-per-use tariffs, which results in lower usage of service for their particular application. These results suggest that consumers make mistakes while maximizing their surplus from the consumption of access services, and pricing structures influence the types of mistakes they make. Identifying the mistakes and the behavioral biases that determine this consumption behavior has important ramifications for pricing and optimal contract design.

Purchasing access services typically occurs in advance of consumption when consumers are generally uncertain about how much they will use the service and/or how valuable usage opportunities are. This uncertainty makes the consumption problem quite complicated for the consumer. In this paper, we investigate how different contractual forms affect in-contract consumption decisions. In contrast to the earlier literature, we model the consumption process in detail and analyze the consumer behavior *after* the purchase of the contract. In particular, we are interested in answering the following questions: 1) Is there a plausible heuristic that consumers use to make daily consumption decisions? 2) Given the heuristic used, does contractual form affect consumption behavior? 3) Do decision biases lead to substantially different consumption behavior under certain contractual forms? 4) What are the implications of the interaction effect between contractual form and consumption for the firms?

To that end, we develop a theoretical model of consumption behavior for an individual who faces a sequence of consumption opportunities, and has been endowed with a price contract. This model identifies the optimal consumption policy, as well as a nearly optimal heuristic. Furthermore, we identify how consumption would shift under biases such as the over-(or under-) estimation of consumption values, risk aversion, regret aversion, the sunk cost fallacy and the taxi meter affect (a physiological transaction cost such as distaste for payment at the time of consumption) .

We test our theoretical model by conducting a laboratory experiment where subjects repeatedly perform a dynamic consumption "cell phone task". In each task subjects are endowed with a number of free phone calls (and charged an access fee), and then receive 30 calls whose value is drawn randomly. For each call subjects decided whether to answer the call (and either use a free call, or be charged the per-unit cost). We find that a majority of subjects use a threshold policy, and those that do not have substantially lower earnings. We also find that subjects on average use the correct threshold policy when they do not have any free calls. Subjects also adjust their threshold in the correct direction as the optimal threshold (and nearly optimal heuristic) changes as the remaining time and included free units in the contract deplete. We find that the nearly optimal heuristic matches their choices somewhat more closely than the optimal policy. However, in line with previous empirical research, they are too aggressive in using their free calls, which leads to sub-optimally answering too many calls, and answering too many calls of low value. These mistakes cost subjects up to 20% of their payoff, and subjects continue to make these mistakes even after repetition of the consumption task.

We also measure subjects' beliefs about the value distribution, their risk aversion, their regret aversion and their propensity towards the sunk cost fallacy, as well as a measure of cognitive ability. Previous research on the preference for contracts providing free units have suggested that risk attitudes and the sunk cost fallacy may drive this contract-choice bias, so we examine if these mechanisms can also affect consumption behavior. Mistaken beliefs shift consumption in an intuitive manner. Specifically, subjects who underestimate the value of future calls (either by underestimating the frequency of high value calls or overestimating the frequency of low value calls) are more liberal in using their free calls. Other biases such as risk aversion and the sunk cost fallacy do not affect consumption behavior, although individuals with lower cognitive ability are too conservative when they are given a pay per unit plan. In a second experiment we provide subjects with the full call value distribution, and again find that subjects significantly overuse their free units.

We then run a third experiment where we can directly measure subjects' willingness to pay for the contract with free calls (instead of the pay-per-use contract). When we offered the 10 Calls contract, we find that almost 50% of subjects are willing to pay full price or more (i.e. pay in advance at least as much as it would cost to answer the calls under pay-per-use contract), with 21% of subjects willing to pay more than the pay-per-use price. Strikingly, this latter group increases over time to 27% in the fourth repetition. When offered 20 Calls contract, more than 40% of subjects are willing to pay at least the pay-per-use price, with 8% willing to pay more. Pre-purchasing the 20 Calls contract sacrifices substantial option value relative to the pay-per-use contract, as only 51% of subjects receive 20 or more calls worth at least $ 0.35.

We also find that in the 10 Calls WTP treatment the subjects who value free calls the most are also those who answer the fewest calls under a pay-per-use contract. Therefore, offering a contract with a three part tariff has three benefits to the firm: price discrimination, sorting consumers into their highest-revenue contract, and increasing the usage of consumers with free calls. We do not find a similar sorting effect in the 20 Calls WTP treatment, indicating that the sorting behavior may be affected by the menu of contracts available.

We then calculate the optimal access fee (i.e. the revenue-maximizing price for the firm given average consumer behavior under each kind of contract), and find that the optimal discount from the full pay-per-unit cost is very small. With the optimal fee, the firm increases revenue by 15% by offering the 10 Calls contract, and increases revenue by 8% by offering the 20 Calls contract, compared to only offering a pay-per-use contract.

The rest of the paper proceeds as follows. Section 2 discusses the existing literature. Section 3 presents the theoretical model of dynamic decision-making and develops a decision heuristic that is asymptotically optimal. We also present the theoretical predictions on the consumption of a consumer who is risk averse, over (under) estimating and has sunk cost fallacy. Section 4 describes the design of our main experiment, while Section 5 presents and analyzes the results. We discuss our robustness-check experiment in Section 6, and the willingness-to-pay experiment in Section 7. Lastly, we discuss our results and conclude in Section 8.

2 Literature Review

We first survey the existing literature on price discrimination in access service industries. Most of the literature in this area assumes there are multiple types of consumers that differ in their taste for consumption, and that a monopolist firm offers a menu of pricing contracts to induce consumers to self-select into the appropriate contract given their type. Examples of non-linear pricing contracts used in the telecommunications and utilities markets include pay-per-use contracts; two-part tariffs with an access fee and a per-unit usage price; three-part tariffs with an access fee, some number of free units and a pay-per unit usage price; and unlimited usage contracts (see Wilson 1993 and Tirole 1988 for a review of the economics literature on non-linear pricing).

Typically consumers must select the pricing contract significantly in advance of the consumption decisions, which introduces consumer uncertainty about future demand and consumption valuations. At the time of the contract choice, the consumer has an estimate over her usage during the contract duration but does not know the exact amount and the value of each consumption opportunity. Many papers have analyzed the effects of demand uncertainty and measured its effects on pricing. Miravete (2002) estimates a structural econometric model of demand for fixed-line telephone service for a provider that offers a two-part tariff and a flat-rate tariff, allowing for uncertain future consumption. Lambrecht, Seim and Skiera (2007) find that it is ex-ante optimal to choose a tariff with a higher usage allowance than would be optimal if they were not uncertain over their demand.

The advance pricing and revenue management literature also suggests non-linear pricing solutions for one time use services such as event tickets and air transportation (Xie and Shugan 2001, Gallego and Sahin 2010). The fundamental assumption of all these papers is that consumers are rational decision makers who seek to maximize their surplus. Moreover, this literature focus on the contract purchase decisions rather than ex-post consumption behavior. Recently an operations management literature has developed studying access service pricing using a queuing framework where the service system may be congested. Most of this literature studies pay-per use pricing, with a few exceptions that study subscriptions (access fee with unlimited usage). Randhawa and Kumar (2008) compare per-use pricing with subscription pricing that imposes usage limits (similar to Netflix's policy). Cachon and Feldman (2011) compare pay-per use and subscription pricing when there are congestion costs. Bitran, Rocha e Oliveira and Schilkrut (2008) study two-part tariffs where the firm's pricing policy and service level (quality) affects the dynamics of their system over time through customer satisfaction. In our study, consumers do not experience congestion costs, and we compare ex-post consumption behavior under a pay-per-use contract and a three part tariff. These types of contracts are common in car leasing, telecommunication services, utilities where system congestion is rarely an issue for the consumer.

Another body of work focuses on decision biases and mistakes in tariff choice. This literature has found that the consumers often make mistakes in tariff choice (Kridel, Lehman, and Weisman 1993; Miravete 2002, Train, McFadden, and Ben-Akiva 1987, DellaVigna and Malmendier 2006; Nunes 2000). In particular, the behavioral literature has found that consumers exhibit a biased preference for choosing a flat rate contract (unlimited usage plans) over a pay-per-use option even if it leads to a lower consumption value. Lambrecht and Skiera (2006) identify risk aversion, demand over-estimation, and a distaste for paying per consumption ("taxi-meter" effect) as possible causes of the flat rate bias. DellaVigna and Malmendier (2006) show that health club users overestimate their future usage by more than 100% and subsequently tend to choose flat rates over pay-per-use contracts. Several other papers consider the effect of other consumer biases such as self control problems on optimal nonlinear pricing (DellaVigna and Malmendier 2004, Oster and Scott Morton 2005, Esteban and Miyagawa 2007, Plambeck and Wang 2011). Note that all of these papers study static contract choice while we study the dynamic consumption decisions and mistakes of consumers after the contract choice.

Recent empirical work has shown that within-month consumption is strongly affected by the contract terms beyond what can be explained by the change in marginal prices and budget constraints. In particular, Ascarza, Lambrecht and Vilcassim (2009) estimate that within individuals demand satiation increases by 31.5% under a three-part tariff (after controlling for budget effects). Ascarza et. al point out that a pricing plan may have attributes that alter and influence the consumer's usage decisions. To that end we model consumers who are uncertain about their consumptions and make usage decisions taking into account the remaining balance of included free units and time in their contract. This is an improvement over the existing literature which do not typically looks into post tariff behavior. Grubb and Osborne (2011) and Yao, Mela, Chiang and Chen (2011) are two exceptions that analyze in contract consumer decisions using cellular-phone data. We discuss how our findings support and differ from those in Section 8.

In summary our work is the first experimental paper that focuses on the effect of decision heuristics and biases on the post tariff choice consumption decisions. We compare three part tariffs to pay-per-use and focus on the impact of over (under) estimation of consumption values, risk aversion, regret aversion and the sunk cost and taxi meter effects on the dynamic consumption decisions and heuristics. Finally, we examine firm's optimal contract.

3 Consumer Behavior and Theoretical Predictions

We will first present our theoretical model and predictions. We study a three part tariff (x, c, p) where x is the access fee, c is the number of free units (initial allowance), p is the non-negative per unit fee for any consumption over initial allowance. The coverage period of the contract is assumed to be T periods. The consumer pays fixed cost x for the right to use the service and c free units. If her consumption turns out to be more than c, she pays a per unit fee p for each additional unit. Notice that pay per unit contract $(0, 0, p)$ is a special case. We are interested in in-contract consumption behavior and how the contract terms influence this behavior. We do not study the contract purchase decisions and the optimal menu of contracts.

Consumers are uncertain about their exact consumption levels $N(t)$, $0 \leq t \leq T$ and the value of each consumption, V. Whenever a consumption opportunity arises, consumers observe the actual value of the opportunity and decide whether to consume a unit of service. First we consider a risk neutral rational consumer who is uncertain about her consumption level and value of each consumption opportunity. Consumption opportunities arise sequentially over time. She extracts utility V from the consumption of each free unit. If she uses the service when she does not have any free units, she pays pay-per-unit price p resulting in net benefit of $V - p$. We first study the optimal dynamic consumption policy.

3.1 Dynamic Consumption Model and Optimal Policy

Most individuals use shortcuts and heuristics to maximize their utility from cellular phone, internet or club membership contracts. Here, one of our goals is to identify heuristics that consumers may use. To do this we first solve the discrete time optimal control problem of an unboundedly rational consumer who holds an (x, c, p) contract with duration T. Then we derive easy to compute heuristics that have similar structural properties with this dynamic optimal control problem.

We assume the value of each consumption- V follows a distribution such that a consumption opportunity with value v or less arises with probability $F(v) = P(V \leq v)$ at time t, and the consumer adjusts her consumption strategy dynamically over time. We assume that with probability $F(0)$ no consumption opportunity arises. Each consumption uses one unit of service. With k units left and t periods to go, the expected utility is given by

$$
\begin{aligned}
J(k,t) &= E[\max\{v + J(k-1,t-1), J(k,t-1)\}], \quad k > 0, t \geq 1 \\
J(k,t) &= tE(V-p)^{+} \quad k \leq 0, t \geq 0.
\end{aligned}
$$

If there are t periods to go until the contract coverage ends, with probability $\bar{F}(0)$ a consumption opportunity arises. Consumer observes the value of the service and decides whether to use the service or not. If there are free units left in the contract and the consumer uses a free unit, then her total expected utility is $v + J(k-1,t-1)$ where $J(k-1,t-1)$ is the optimal expected utility with $k-1$ free units and $t-1$ periods to go. Otherwise, the consumer's expected utility is given by $J(k,t-1)$. If she has no free units left and there are t periods to go until the contract expires, she uses the service only if $V \geq p$ resulting in expected utility $tE(V-p)^{+}$. With some algebra we obtain:

$$
J(k,t) = J(k,t-1) + E[\max\{v - \Delta J(k,t-1), 0\}]
$$

where $\Delta J(k,t) = J(k,t) - J(k-1,t)$ with boundary condition $J(k,0) = 0$.

Theorem 1 shows that the decision maker uses the service if the value of the service is greater than $\Delta J(k,t)$ which is the opportunity cost of the kth unit with t periods to go. The threshold is a function of the pay-per-unit fee, the number of remaining free units, and remaining time until contract expires.

Theorem 1 [1] *It is optimal to use the service if and only if $V \geq \Delta J(k,t)$. Moreover i) $J(k,t)$ is increasing in k and t, ii) $\Delta J(k,t)$ is decreasing in k and is increasing in t, iii) $\Delta J(k,t)$ is increasing in p.*

The first part of Theorem 1 states that the expected utility is increasing in the number of remaining free units, and the remaining time in the contract. The last two parts of the theorem shows that the threshold is decreasing in the number of remaining units, increasing in the remaining time t and per unit price p.

[1] Papastavrou, Rajagopalan, and Kleywegt (1996) show a similar result for the problem with $p = \infty$. We omit the proof of this result. The proof is similar to Papastavrou et. al and available from the authors for continuous and discrete valuation distributions as well as for a continuous time model with Poisson arrivals.

Although a rational individual who has infinite computational ability uses the dynamic threshold policy over time, it is unlikely that a consumer would have the ability to compute and update this threshold optimally over time. However, this policy suggests plausible heuristics that consumers may use. We discuss three heuristics in the following section.

3.2 Heuristic Policies

In this section we study three heuristic policies: i) a myopic policy, ii) a totally static threshold policy and iii) a static threshold with adjustments policy. The myopic and totally static policies are previously studied by Liebman and Zeckhauser (2004) and Borenstein (2009) respectively. Here we show the connection of the totally static policy to the optimal policy, and then we propose another heuristic, the static threshold with adjustments, which is the dynamic version of the totally static policy. This decision rule is structurally similar to the optimal policy but easier to compute and results in higher consumer surplus than myopic and totally static policies. In Section 5 we investigate which of the three heuristic policies fit consumption decisions in a cell phone experiment.

With the myopic policy, or spotlighting (Liebman and Zeckhauser (2004)), consumers focus on the instantaneous costs and payoffs in the current period without considering the effects of the current period decision for the remainder of the contract duration (i.e.,opportunity cost of the current decision). Thus consumers of an (x, c, p) contract over T periods use zero as the threshold when they have free units (i.e. use a free unit for any consumption opportunity that has a positive value) and use p as the threshold when they run out of free units (use a unit if the value of the consumption opportunity is greater than the per unit cost p).

The totally static policy, first proposed by Borenstein (2009) and used by Grubb and Osborne (2011), assumes that the consumer picks a threshold at the beginning of the consumption horizon and uses this threshold to filter the consumption opportunities over time.[2] We derive a static heuristic policy that is asymptotically optimal as the free units in the contract and the number of consumption opportunities grow. The static threshold with adjustments uses for each consumption opportunity the totally static threshold that applies for the remaining time.

[2]In the context of electricity markets, Borenstein (2009) explains this policy as the "behavioral rule" consumers use to make decisions about their consumption patterns before the consumption period begins. During the consumption period exogenous shocks to the quantity demanded occur, but consumers do not change their behavior in response.

A static heuristic is appealing because if an individual uses the same static threshold (behavioral rule) in all decisions until the expiration of the contract, this simplifies the utility maximization problem of the previous section. With this policy, the consumer uses the service if its value is greater than threshold- q if she has free units. Then she filters the consumption opportunities by p if she has no free units. The expected utility of a free unit given the value of consumption is greater than q is given by $E(V|V > q)$. If the consumer has to pay for the service than the expected utility is $E(V - p)^+$. Combining these two terms, we obtain the expected utility of a consumer who uses the *same* static threshold rule:

$$J^s(k,t) = \max_{q \leq p} \; J^s(k,t,q) = E(V|V > q)\min(t\bar{F}(q), k) + E(V-p)^+ \frac{(t\bar{F}(q) - k)^+}{\bar{F}(q)}.$$

where $\bar{F}(q) = P(V \geq q)$. Note that the consumer considers only the expectation of the consumption (ignores the fact that with threshold q consumption is a Binomial random variable with t and $\bar{F}(q)$), therefore the total number of consumption opportunities filtered with q is equal to the expectation $t\bar{F}(q)$. The first term is the utility derived from the consumption of free units, and the second term accounts for the expected utility derived from the paid units. We define $q(k,t) = \min\left\{0 \leq q|\bar{F}(q) \leq \frac{k}{t}\right\}$ as the capacity clearing threshold. Notice that q can not be larger than the per unit price p, so we have $q(k,t,p) = \min\left\{0 \leq q \leq p|\bar{F}(q) \leq \frac{k}{t}\right\}$.

Theorem 2 *$q(k,t,p)$ maximizes $J^s(k,t,q)$.*

Theorem 2 shows that capacity clearing threshold bounded by pay per unit fee maximizes the utility of a consumer who holds a contract with k remaining free units and remaining coverage time t. Surplus of a consumer if she uses the static threshold $q(k,t,p)$ to filter the consumption opportunities is given by $u(k,t,p) = J^s(k,t) - x$. Then the surplus of a consumer who has a contract (x,c,p) is equal to $u(c,T,p) = TE(V - q(c,T,p))^+ + cq(c,T,p) - x$. We have the following structural results regarding the consumer surplus if the consumer uses the static deterministic threshold policy $q(c, \lambda T, p)$.

Theorem 3 *i) $u(c,T,p)$ is increasing and jointly concave in c and T for any fixed p, ii) $u(c,T,p)$ is decreasing in p for any fixed (c,T), iii) $q(c,T,p)$ is decreasing c, iv) $q(c,T,p)$ is increasing in T.*

Confirming the intuition, Theorem 3 states that the surplus increases as the number of free units increases. On the other hand, the consumer uses a smaller (higher) threshold as c (T) increases (decreases). Notice that the static threshold policy mimics the structure of the optimal policy closely (Theorem 1). As the expiration time approaches, expected demand decreases, therefore the consumer uses a lower threshold and uses a free unit for lower valued consumption opportunities. As the number of free units decrease, the threshold increases and the consumer uses a free unit for only higher valued consumptions. One can also show that this deterministic static heuristic is asymptotically optimal (as T and c increases) for the stochastic optimal control problem discussed above.

The threshold heuristic $q(k, t, p)$ is static in the sense that it ignores the uncertainty in the number of future consumption opportunities and assumes the number of opportunities is known. Using this heuristic we can generate the two behavioral predictions for consumers described above. First, consumers may use a totally static threshold - setting a single threshold at the beginning of the consumption period that remains constant. Alternately, consumers may use a static threshold with adjustments - at every consumption opportunity the consumer uses the static threshold that would apply for the remaining time. This means that the consumer does adjust based on the length of time remaining and the number of free units left, but does not account for future adjustments. This increases the expected utility and captures somewhat the dynamic nature of the optimal policy. Next we study how behavioral biases alter the heuristic policies.

3.3 Over(Under) Estimation and Overconfidence

In recent literature, it has been shown that mistaken beliefs on the likelihood of future events may have significant impact on individuals' decisions (Loewenstein et al. 2003, Eliaz and Spiegler 2006, 2008). In our setting, consumer beliefs about the value and the number of consumption opportunities may affect their consumption behavior. The following theorem presents how the threshold of a consumer who over (under) estimates demand or the valuation distribution is different from a rational consumer's threshold.

Theorem 4 *Suppose that V is true valuation distribution and W is consumer's estimation of her valuation distribution. If V first order stochastically dominates W, $V \succeq W$, then $q_W(c, T) \geq q_V(c, T)$.*

If the consumers estimate the upper tail of the valuation distribution to be lighter (heavier) than it is, then they are more conservative (aggressive) in using free units than they are if their estimates are correct with static policy and static policy with adjustments. Because of this mistake, they obtain lower surplus than they would obtain if they knew the true distribution. It is easy to see that over(under) estimation has no effect on the myopic policy.

3.4 Risk Aversion

Previous studies on phone tariff choice have also emphasized the immportance of risk aversion. Miravete (2003) and Train et. al. (1989) find that consumers who are uncertain about their usage rate tend to choose flat rate phone plans to protect themselves from the downside risk of paying too much if their usage rate turns out to be high. Other researchers (Nunes 2000) do not find a relationship between tariff choice and risk aversion. To see the affect of risk aversion on in-contract usage behavior, we study how the threshold policy change if consumers are risk averse in the following theorem. We model risk averse expected utility by introducing diminishing marginal utility for money. We assume $U(y)$ is a continuous function with $U' \geq 0$ and $U'' \leq 0$.

Theorem 5 *Risk averse consumer uses a higher static threshold, $q_{RA}(c, T, p) \geq q(c, T, p)$, when $c > 0$.*

Theorem 5 states that risk-averse individuals use the service/product more conservatively when they have free units to insure against the risk of paying additional fees when all of the free units are used with both static and static with adjustments policies. When they do not have any free units, the consumption behavior of a risk averse individual is not different than a risk neutral individual. Risk aversion has no affect on the myopic policy.

3.5 Sunk Cost and the Taxi Meter Effect

A rational consumer should take into account only current and future costs and benefits while making consumption decisions. However, the psychology and behavioral economics literatures show that individuals often incorrectly pay attention to sunk costs while making decisions (see for example Arkes and Blumer (1985)). In access services, if the contract has an access fee and a number of free units, then the sunk cost of the access fee might affect the consumption decisions of some individuals. Consumer may then feel disutility proportional to the number of residual free units at the contract expiration time. While the optimal static threshold policy should lead consumers to use all free units in expectation, if consumers care about sunk costs the additional asymmetric utility cost for having excess units (compared to having too few unites) may lead them to consume the service more aggressively in order to reduce this disutility.

On the other hand, if the consumer has no free units, or uses all the free units before the contract expiration, she has to pay p whenever she uses the service. Prelec and Loewenstein (1998) argue that coupling the payment with the consumption decreases the utility derived from the service/product. Mental accounting assumes that consumers attribute the disutility of payment for a good directly to the utility derived from its consumption (Prelec and Loewenstein 1998; Soman 2001). Paying per use lessens the utility from consumption, as the distaste of paying is attributed to the consumption at the time of usage. In contrast, payments in advance of consumption decouple consumption from payment. Several other papers in the literature (e.g. Lambrecht and Skiera 2006) call this the "taxi meter effect" and suggest it may be one of the biases that consumers face when choosing among tariffs. Here, we consider whether the consumer acts differently if she has to pay each time she uses the service. We employ the imputed cost and benefit concept as described by Prelec and Loewenstein (1998) to model the taxi meter affect. V is the utility from the consumption and ρp is the experience utility lost due to the imputed cost resulting in net surplus $V - (1+\rho)p$. A consumer chooses to consume if the value of the service is greater than $q = (1+\rho)p$. If the consumer has the taxi meter bias (i.e. if $\rho > 0$), the consumer acts more conservative than a rational individual when consuming costly units (i.e. if $p > 0$), but acts rationally when consuming free units ($p = 0$).

4 Experiment 1: Design

In order to test whether a static threshold policy is a good approximation of individual behavior in a dynamic consumption problem, we designed a laboratory experiment to simulate the cell phone consumption problem. Subjects performed four consumption decision tasks, as well as several tasks designed to identify biases in subject beliefs, risk aversion and the sunk cost fallacy.[3] Lastly subjects filled out a brief demographic questionnaire.

4.1 Cell Phone Consumption Task

In the simulated cell phone consumption task subjects received 30 phone calls. The calls had one of five possible values (drawn randomly) for answering the call: \$0.15, \$0.30, \$0.45, \$0.60,

[3]We also implemented two tasks (based on Zeelenberg et al. 1996 and Zeelenberg and Beattie 1997) designed to identify regret aversion; however we did not observe enough regret averse subjects in our data to study this behavior.

or \$0.75.[4] In order to allow subjects to have potentially biased beliefs about the distribution of call values subjects were not told the exact probabilities of each call value.[5] Instead, before the first consumption task subjects were told that call values would be drawn independently in each period from the same distribution throughout the experiment, and then were allowed to draw sample outcomes from the distribution. Subjects were allowed to draw as many samples as they wished before continuing with the experiment.[6]

In each period we used the strategy method to elicit from the subjects whether they would answer each type of phone call. That is, they were asked (for each call value) if they would want to answer the call or not, and were told that their conditional strategy would be used to answer the call. This allows us to observe a subject's complete consumption strategy for each phone call, rather than only observing the outcome of their decision. Subjects were then told the actual call value and whether they had answered it (according to their stated strategy).

Subjects participated on one of three treatments that defined their cell phone plan. In the "0 Calls" treatment subjects began with zero free calls, but had no "monthly fee". In the "10 Calls" treatment subjects began with ten free phone calls, and had a \$3.50 "monthly fee" deducted from their payoff at the end of the task. In the "20 Calls" treatment subjects began with twenty free calls, and had a \$7.00 "monthly fee". In all three treatments subjects had to pay \$0.35 to answer a call if they did not have any free calls left. Subjects could see both the plan details, as well as the current period and the current number of free calls left, throughout the decision task.

Figure 1 displays what the optimal threshold policy and the optimal static threshold is given the number of free calls left and the number of remaining periods. The two policies are very similar, with the optimal policy answering the \$0.30 call in more cases than the static threshold.

After receiving all 30 calls subjects were informed of their monthly fee, the total value of all calls answered, the total charges for answering calls, and their overall payoff. One of the cell phone tasks was selected randomly for payment.

[4]The call values had the following probabilities: $P(\$0.75) = 0.15, P(\$0.60) = 0.25, P(\$0.45) = 0.25, P(\$0.30) = 0.25, P(\$0.15) = 0.10$.

[5]This assumption is also realistic - consumers are unlikely to know in advance the exact probability that they will receive a certain number of important phone calls in the coming month. Instead consumers must base their beliefs on previous experience of how likely it is they will use a given number of minutes.

[6]To speed up the experiment subjects saw ten random outcomes at a time, and also saw a table of the number of observations of each call value from all of the sampled outcomes.

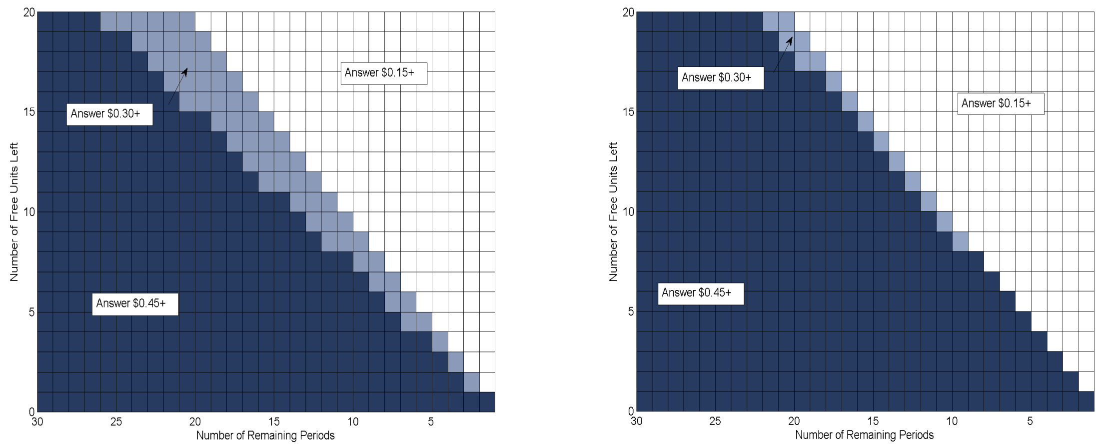


Figure 1: Optimal Threshold Policy (left) and Static Threshold Policy (right)

4.2 Beliefs about the Value Distribution

At the start of each consumption task we elicited subject beliefs about the upper and lower tails of the call value distribution. Subjects were asked to guess how many of the 30 calls would be \$0.75 calls, and how many would be \$0.15 calls. For each guess subjects had \$0.50 added to their task payoff if they were correct, or \$0.25 if they were within 1 of the correct answer.

4.3 Risk Aversion

To measure risk aversion, after the fourth consumption task subjects were asked to perform the paired lottery choice task from Holt and Laury (2002).[7] Subjects were asked to make ten choices between a "safe" lottery and a "risky" lottery. Both lotteries had two potential outcomes (with the risky lottery having a larger difference between the payoffs), and both had the same probability of high and low value outcomes. The probability of the high outcome increased in 10% increments from 10% to 100%. For example in one decision the safe lottery was (30% chance of \$2.00, 70% chance of \$1.60) while the risky lottery was (30% chance of \$3.85, 70% chance of \$0.10). Therefore the safe lottery has a higher expected value when the probability of the high outcome is small, and the risky lottery has a higher expected value when the probability of the high outcome is large. Following Holt and Laury we use the number of safe lottery choices as a measure of risk

[7]We include the diagnostic measures of risk aversion, regret aversion, etc. at the end of the experiment in order to avoid any potential contamination of subjects' consumption behavior - which is the main focus of our study. However, given that these measure have largely no effect on consumption behavior, we do not feel that contamination across tasks distorted behavior in our experiment.

aversion.[8] One of the lottery decisions was randomly selected for payment.

4.4 Regret Aversion

We use two measures of regret aversion, based on Zeelenberg et al. (1996) and Zeelenberg and Beattie (1997). Both measures exploit the fact that a regret averse individual does not like to discover that the choice she made led to a worse outcome than another possible option. Our first measure presents subjects with two additional lottery choices, with the probabilities set (based on the subject's previous lottery choices) so that the subject should be roughly indifferent between the two lotteries. However, for these two choices the subject will be informed of the outcome of the safe lottery or the risky lottery, in addition to whichever lottery they chose. Therefore, a regret averse individual should choose the safe lottery for the first choice, and the risky lottery in the second choice - i.e. she should choose the lottery that she will already be informed about. This means that the subject will not be able to compare the outcomes, and therefore will avoid regret.

The second measure uses two ultimatum game choices. For the first game, proposers will only be told if the responder accepted or rejected her offer. For the second game, proposers will also be told the smallest offer the responder would have accepted. Zeelenberg and Beattie (1997) show that in the second case regret averse proposers make more aggressive (i.e. lower) offers to avoid the regret of making a higher offer than is necessary to avoid rejection. All subjects make decisions both as proposers and as responders for both games.

4.5 Sunk Cost

To identify subjects exhibiting the sunk cost fallacy we asked subjects to make a decision for a hypothetical scenario adapted from Arkes and Blumer (1985). In the scenario subjects were told that they had accidentally bought tickets for two ski trips on the same weekend. They had paid more for one trip, but expected to enjoy the other trip more. They were told they could not return either ticket, and were asked to choose which trip they would go on. Therefore, subjects who say they would go on the less enjoyable trip that they had paid more for exhibit the sunk cost fallacy.

[8] As in Holt and Laury many of our subjects do not have a single decision where they switch from choosing the safe lottery to choosing the risky lottery.

4.6 Cognitive Ability

For a subset of our sessions we also included a simple measure of cognitive ability. We asked subjects to solve the three question *cognitive reflection task* from Frederick (2005). Each of the three questions has an intuitive, but incorrect, answer, while seeing the correct answer takes somewhat deeper thinking. Frederick argues that the CRT score is a simple measure of a kind of cognitive ability that correlates well with decision-making heuristics and biases such as present-biased inter-temporal preferences and risk-seeking to avoid losses. The CRT score also correlates well with SAT and ACT scores. Subjects in our experiment were paid \$0.25 for each correct answer.

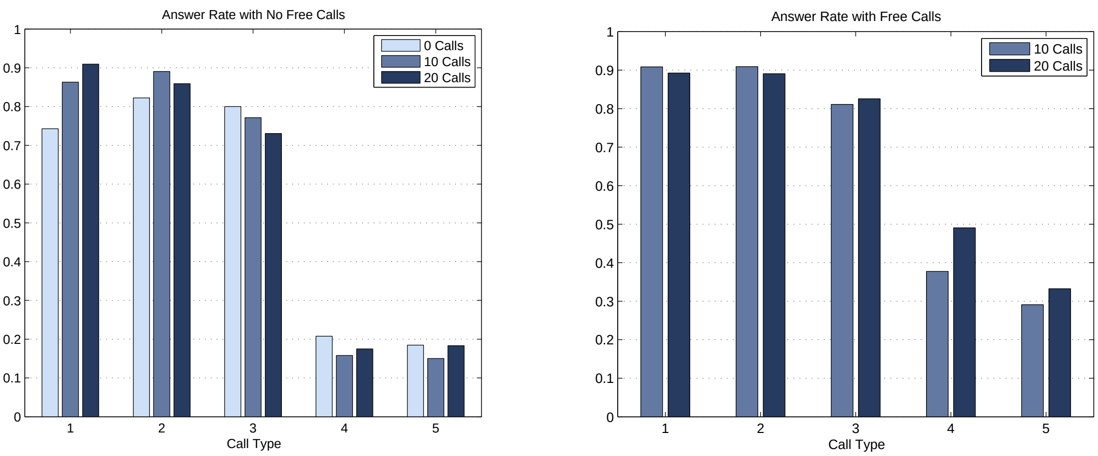
5 Experiment 1: Results

We had a total of 104 students at the University of Michigan participate as subjects, with 36 subjects in the 0 Calls treatment, 36 subjects in the 10 Calls treatment, and 32 subjects in the 20 Calls treatment.[9] Sessions lasted approximately 50 minutes, and subjects earned \$12.94 on average.

5.1 Call Answer Decisions

We first examine subjects' consumption decisions. Figure 2 displays for each call type within each treatment the percent of decisions to answer the call. Furthermore, we display the answer rates for decisions with and without free calls separately. Answer rates without free calls are similar across all treatments: subjects answered the three highest call types in 70% to 90% of decisions, while they answered the two lowest call types in 10% to 20% of decisions. Similarly, when subjects have free calls they answer the three highest value calls in 80% to 90% of decisions. However, subjects answer the lowest value calls at substantially higher rates: answering between 30% and 50% of these low value calls.

[9]Three subjects in the "10 Calls" treatment had to be dropped from the analysis due to a technical problem in the first session.



The $0.75 call is denoted as call type 1, the $0.60 call is denoted as call type 2, etc.

Figure 2: Answer Rates with and without Free Calls

5.2 Use of a Threshold Policy

We next want to examine whether subjects use a threshold policy in making answering decisions. Table 1 displays for each treatment the percent of periods in each task where subjects used a threshold policy to answer calls, as well as the percent of subjects who use a threshold policy throughout the task.[10] Overall subjects used a threshold policy for the majority of their decisions, however somewhat fewer subjects used a threshold for every decision in a task.[11] Furthermore, subjects appeared to learn to use a threshold policy: subjects in the 10 Calls and 20 Calls treatments were significantly more likely to use a threshold policy throughout the experiment in Task 4 than they were in Task 1 (test of proportions: $p < 0.01$ and $p = 0.02$). Subjects in the 0 calls treatment were also somewhat more likely to use a threshold policy throughout ($p = 0.09$). Additionally, cognitive ability appears to play a role in whether a subject consistently uses a threshold policy. In the 0 calls treatment subjects who got zero correct in the CRT used a threshold throughout the task in 46% of tasks, compared to 78% for subjects who got all three questions correct (non-parametric test for trends: $p < 0.01$). Similarly in the 10 and 20 calls treatment, only 38% (13%) who got zero correct consistently used a threshold, compared to 95%

[10] The second total column shows the percent of subjects who use a threshold policy in each period of all four tasks.

[11] While in these data the subjects in the 0 Calls treatment are less likely to use a threshold policy, this does not appear to be a robust result. Subjects in Experiment 3 with a 0 Calls contract are at least as likely to use a threshold as other subjects. This is true for the subset of subjects who faced very high random prices (ruling out sorting effects).

(75%) who got three questions correct ($p < 0.01$ for both).

Table 1: Usage of Threshold Policies

	% of Decisions with Threshold Policy					% Subjects Always Using Threshold Policy				
Treatment	**Task 1**	**Task 2**	**Task 3**	**Task 4**	**Total**	**Task 1**	**Task 2**	**Task 3**	**Task 4**	**Total**
0 Calls	66%	64%	72%	79%	71%	53%	58%	69%	72%	53%
10 Calls	77%	89%	91%	91%	87%	58%	79%	85%	88%	55%
20 Calls	78%	79%	83%	91%	83%	47%	69%	69%	75%	44%

5.3 Answer Policies

We now examine the answer policies for subjects who used a threshold policy. Since these subjects are using thresholds, we will characterize an answer policy by the number of call types the subject has chosen to answer. For example, an answer policy equal to 3 means the subject wishes to answer any call worth \$0.45 or more. Figure 3 shows for each treatment what the average answer policy was in each period, as well as the average number of free calls remaining in each period.

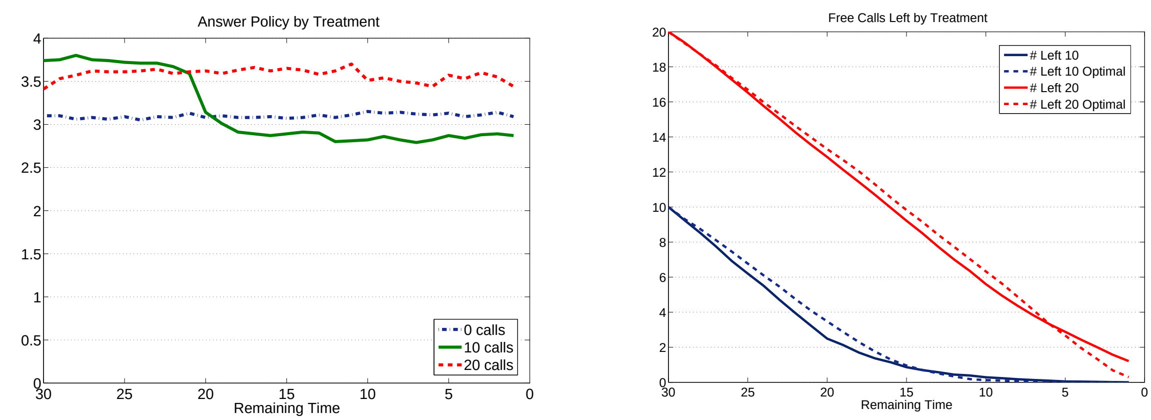


Figure 3: Answer Policy and Free Call Usage

In the 0 Calls treatment subjects are on average choosing an answer policy very close to their dominant strategy (answering any call worth at least \$0.45) throughout the task. Subjects choose to answer fewer call types only 6% of the time, and choose to answer more call types only 10% of the time. In the 10 Calls treatment subjects begin by answering on average all but the lowest value of calls. This quickly uses up all of their free calls - subjects on average use their last free call in period 15. Afterwards subjects act very similarly to those in the 0 Calls treatment, on average answering any call worth at least \$0.45. Similarly, in the 20 Calls treatment subjects begin by answering on average slightly more than 3.5 call types. However, because their free calls last much longer (until period 26 on average), subjects in this treatment continue to answer approximately 3.5 call types on average throughout the task. Overall the average answer policy is 0.5 higher when subjects have free calls left (2.97 with zero calls left vs. 3.55 with one or more calls left). This is quite different from the myopic policy of answering all calls, and much closer to the static threshold policies.

Table 2: Answer Policy

VARIABLES	Coefficient	Std. Error
# Periods Left	-0.00436***	(0.00101)
10 Calls Treatment & 0 Calls Left	-0.165	(0.140)
20 Calls Treatment & 0 Calls Left	-0.294*	(0.178)
10 Calls Treatment & 1+ Calls Left	0.577***	(0.148)
20 Calls Treatment & 1+ Calls Left	0.657***	(0.176)
Task #2	0.0428**	(0.0212)
Task #3	0.0799***	(0.0202)
Task #4	0.000379	(0.0204)
Constant	3.091***	(0.0965)
Observations	9681	
Number of Subjects	100	

Robust standard errors reported in parentheses. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The dependent variable is the subject's answer threshold. The constant term reflects the policy in the 0 Calls treatment. The specification is OLS with subject random effects, and the observations are restricted to periods where the subject used a threshold policy.

Table 2 reports the results of regressing subjects' answer policies on treatment dummies (with and without free calls), task dummies and the number of remaining periods. The answer policy with zero free calls is not significantly different from 3 for any of the treatments in any period ($p > 0.10$ for all comparisons). The answer policy with one or more free calls is significantly larger than 3.0 for both the 10 Calls and 20 Calls treatment ($p < 0.01$ for both comparisons), and the 10 Calls and 20 Calls treatments are not significantly different ($p = 0.67$). There does not appear to be a consistent monotonic trend in the answer policy across the consumption tasks.

5.4 Comparison to Optimal Policy

We now compare our experimental results to behavior under the optimal policy, and to the optimal totally static and static with adjustment threshold policies. Subjects' answer policies match the optimal threshold exactly in 62.4% of decisions, including 41.6% of decisions with 1 or more free calls. Similarly, decisions exactly match the static threshold with adjustments policy in 63.9% of decisions, including 44.8% of decisions with 1 or more free calls. In our data the optimal policy and the static threshold with adjustments policy coincide for 100% of decisions in the 0 Calls and 10 Calls treatment, and coincide for 89% of decisions in the 20 Calls treatment. When the optimal threshold and the static threshold with adjustments policies differ, subject's match the optimal threshold in 9.8% of decisions, while they match the static threshold with adjustments policy in 50.7% of decisions (this difference is significant: signed rank test $p < 0.01$). This suggests that both the optimal threshold and the static threshold with adjustments are good predictors of behavior, however the static threshold with adjustments policy matches behavior more closely.

We can also demonstrate that subject's answer thresholds respond to the decision features that affect the optimal and static thresholds. Column 1 of Table 3 reports the results of regressing subjects' answer policies on dummy variables for the optimal policy. Column 2 reports the same regression for the static threshold with adjustments policy. In both regressions subjects' answer policies significantly increase when the optimal policies increase (i.e. the subject has many free calls left relative to the number of remaining periods). The second specification makes clear that subjects do not use a totally static threshold.

Table 3: Comparison to Optimal Policy

VARIABLES	(1)	(2)
# Periods Left	0.0184***	0.0176***
	(0.000832)	(0.000848)
Optimal Policy = 4	0.400***	0.520***
	(0.0608)	(0.179)
Optimal Policy = 5	1.553***	1.453***
	(0.0841)	(0.0818)
Constant	2.937***	2.964***
	(0.0801)	(0.0804)
Observations	9681	9681
Number of Subjects	100	100

Robust standard errors reported in parentheses. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. Column 1 uses the optimal threshold policy as the independent variable, while Column 2 uses the optimal static threshold with adjustments policy. The specification includes subject random effects, and the observations are restricted to periods where the subject used a threshold policy.

We can also compare the task-level outcomes of subjects to the outcomes that would be obtained by using the optimal threshold throughout the task. Table 4 reports for each treatment the number of answered calls and the average payoff under the optimal policy, as well as the averages observed for all subjects and for subjects who used a threshold policy throughout the task.

Table 4: Comparison to Optimal Policy Outcomes

	Optimal Policy		All Subjects		
Treatment	Answered Calls	Avg. Payoff	Answered Calls	Avg. Payoff	% Sub-Optimal
0 Calls	19.40	\$4.37	17.45	\$3.23	89%
10 Calls	19.20	\$4.33	19.11	\$3.55	90%
20 Calls	21.05	\$4.33	21.20	\$3.17	95%
	Optimal Policy		**Always Use Threshold**		
Treatment	**Answered Calls**	**Avg. Payoff**	**Answered Calls**	**Avg. Payoff**	**% Sub-Optimal**
0 Calls	19.32	\$4.35	19.82	\$4.28	82%
10 Calls	18.98	\$4.26	19.60	\$3.97	87%
20 Calls	21.12	\$4.39	22.24	\$3.95	94%

Subjects in the 0 Calls treatments earn significantly less than the optimal policy (t-test: $p < 0.01$). The majority of this difference is because subjects who do not use threshold policies answer too few calls ($p = 0.01$), however even those who always use a threshold policy earn less than the optimal amount ($p < 0.01$). In the 10 Calls treatment subjects who consistently use a threshold policy earn substantially higher payoffs, but even these subjects answer too many calls ($p = 0.05$) and earn significantly less than they would if they used the optimal policy ($p < 0.01$). In the 20 Calls treatment subjects also answer significantly more calls than is optimal ($p = 0.10$ for all subjects, $p < 0.01$ for subjects who always use a threshold), and earn significantly less than the optimal payoff ($p < 0.01$ for both), although subjects who use a threshold policy earn 90% of the optimum. Furthermore, in both the 10 Calls treatment and 20 Calls treatment subject mis-allocate their calls: the average value the answered calls of threshold-using subjects is significantly lower than the optimum ($p < 0.01$ for both), i.e. subjects answer too many low value calls relative to high value calls.[12]

As Figure 3 makes clear[13], much of the deviation from the optimal policy occurs because subjects

[12]We find similar results by comparing actions to the static threshold with adjustments policy - more than 65% of subjects received a suboptimal payoff in the 10 Calls and 20 Calls treatment, due to answering significantly too many low value calls ($p < 0.01$ for both)

[13]The graphs for the optimal policy account for the actual sequence of call values the subjects saw.

are using their free calls faster than in the optimal policy. Figure 4 shows the percentage of subjects in each period who have fewer calls in each period than the optimal policy. In the 10 Calls treatment between 40 and 50% of subjects have too few calls during the first half of the task, while in the 20 Calls treatment between 30 and 50% of subjects have too few free calls throughout the task.

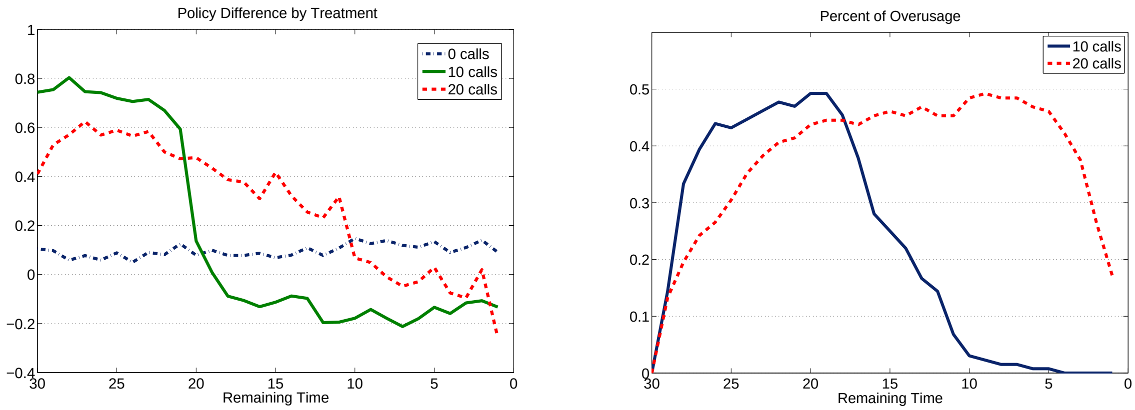


Figure 4: Average Deviation from Optimal Policy and Average Overusage of Free Calls

We can also compare each individual decision to the optimal policy given the number of free calls left and the number of remaining periods. This will account for the 11% of period where it is optimal to answer 0.30 or 0.15 calls. Figure 4 displays for each treatment the average difference between subjects' actual answer policy and the optimal policy in each period. Confirming our previous analysis, we find that subjects in the 10 and 20 Calls treatment answer too many calls early in the task (when they still have free calls left). When subjects do not have any free calls they use a policy close to the optimum. We confirm these results by regressing the difference between the actual and optimal policy on the number of remaining periods, treatment dummies and dummies for having 1 or more free calls left. The results are reported in the first column of Table 5. We also report in the second column the difference between the actual policy and the static threshold with adjustments policy.

5.5 Determinants of Overuse

We now examine what behavioral factors can help explain why subjects overuse their free calls. We examine mistaken beliefs, risk aversion, regret aversion, the sunk cost fallacy, and cognitive ability.

Table 5: Deviations from Optimal Policy

VARIABLES	(1)	(2)	(3)	(4)
# Periods Left	0.00784***	0.00541***	0.00766***	0.00766***
	(0.000970)	(0.000994)	(0.000967)	(0.000967)
10 Calls Treatment & 0 Calls Left	-0.0808	-0.0988	-0.115	-0.113
	(0.148)	(0.148)	(0.147)	(0.146)
20 Calls Treatment & 0 Calls Left	-0.334*	-0.317*	-0.494**	-0.498***
	(0.193)	(0.191)	(0.193)	(0.193)
10 Calls Treatment & 1+ Calls Left	0.489***	0.506***	0.462***	0.464***
	(0.156)	(0.156)	(0.155)	(0.155)
20 Calls Treatment & 1+ Calls Left	0.323*	0.437**	0.182	0.178
	(0.191)	(0.190)	(0.190)	(0.190)
$0.75 Guess - E[# $0.75] & 0 Calls Treatment			0.0155***	0.0160***
			(0.00595)	(0.00584)
$0.75 Guess - E[# $0.75] & 10 Calls Treatment			-0.0233***	-0.0241***
			(0.00823)	(0.00823)
$0.75 Guess - E[# $0.75] & 20 Calls Treatment			-0.00851	-0.00668
			(0.0102)	(0.0102)
$0.15 Guess - E[# $0.15] & 0 Calls Treatment			-0.0165*	-0.0172*
			(0.00976)	(0.00948)
$0.15 Guess - E[# $0.15] & 10 Calls Treatment			0.0109	0.0112
			(0.00884)	(0.00883)
$0.15 Guess - E[# $0.15] & 20 Calls Treatment			0.0524***	0.0524***
			(0.00855)	(0.00848)
Task Controls	YES	YES	YES	YES
Constant	-0.0921	-0.0593	-0.0948	-0.0975
	(0.103)	(0.103)	(0.106)	(0.105)
Observations	9681	9681	9681	9681
Number of Subjects	100	100	100	100

Robust standard errors reported in parentheses. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The dependent variable in columns 1, 3 and 4 is the difference between the subject's answer threshold and the optimal threshold. The dependent variable in column 2 is the difference between the subject's answer threshold and the optimal static threshold with adjustments policy. The specification includes subject random effects, and the observations are restricted to periods where the subject used a threshold policy. The constant term reflects the policy in the 0 Calls treatment. Column 2 uses the true expectation, while Column 3 uses the expectation derived from the subjects' sample of outcomes.

5.5.1 Beliefs about the Value Distribution

Subjects tend to overestimate the frequency of both high value \$0.75 and low value \$0.15 calls, even after controlling for their initial outcome sample. On average subjects guessed 0.85 more high value calls and 2.17 more low value calls than they should expect based on the proportion observed in the sample - both are significantly greater than 0 (t-test: $p < 0.01$, $p < 0.01$). 35 percent of subjects overestimate the number of high value calls by at least 1, while 66 percent of subjects overestimate the number of low value calls by at least 1. Furthermore, many subjects incorrectly believe the distribution is symmetric: 30% guessed that there would be an equal number of low and high value calls.

Column 3 of Table 5 includes the difference between subjects' guesses and the true expected number as an additional control, while Column 4 uses the difference between the guesses and the expected amount based on the subjects' initial sample.[14] Subjects who have mistaken beliefs (by either measure) have significantly different answer policies - in particular subjects with beliefs that imply undervaluing future consumption opportunities are significantly more aggressive in using free calls. In the 10 Calls treatment this effect comes primarily from subjects who underestimate the number of high value calls, while in the 20 Calls treatment it comes mostly from subjects who overestimate the number of high value calls.[15]

Subjects' mistaken beliefs appear to be quite persistent throughout the experiment. While beliefs become somewhat more accurate after the first task, the distribution of the \$0.75 and \$0.15 beliefs are not significantly different in the last two tasks (rank-sum test: $p > 0.60$ for both), with the average of both beliefs significantly larger than zero (t-test: $p < 0.01$ for both). This suggests that subjects are not approaching correct beliefs over the course of the experiment. Furthermore, the error in subjects' beliefs was not significantly correlated with the number of sample outcomes they examined.[16]

[14]We find essentially the same results if we instead use the deviation from the static threshold policy

[15]While there are significant coefficients for the 0 Calls treatment, the two effects tend to cancel for most subjects. Only 3% of subjects have a predicted beliefs effect of -1.0 or less, and another 2% have a predicted effect of 1.0 or more

[16]The median sample size was 100 outcomes. The rank correlations between guess and sample size were $\rho = 0.0492$ and $\rho = -0.0714$ ($p = 0.32$ and $p = 0.15$, respectively).

5.5.2 Risk Aversion

We follow Holt and Laury and used the number of safe lottery choices as our measure of risk aversion. As is typical, a majority of our subjects are risk averse, with 55% choosing the safe lottery at least six times. Column 1 of Table 6 includes a control for risk aversion (the number of safe choices) for each treatment separately.[17] We find that risk aversion does not significantly predict deviations from the optimal policy in any treatment, despite the fact that the optimal policy was determined for a risk neutral consumer.

5.5.3 Regret Aversion

We find that 15% of subjects are regret averse under the lottery measure, and 19% of subjects are regret averse under the ultimatum game measure. Column 2 of Table 6 includes the lottery measure as an additional control, while Column 3 includes the ultimatum game measure. However, it does not appear that either measure of regret aversion is significantly predictive of consumption behavior.

5.5.4 The Sunk Cost Fallacy and the Taxi Meter Effect

In our sample 28% of subjects exhibit the sunk cost fallacy. We include a dummy for subjects who exhibit the sunk cost fallacy in Column 4 of Table 6. However, the consumption behavior of subjects with the sunk cost fallacy does not significantly differ from subjects without the fallacy. We do not find evidence of a substantial taxi meter effect on average consumption behavior, as subjects on average use the optimal answer policy when they do not have free calls (and therefore have to pay an additional cost for each answered call). If a taxi meter effect influenced consumption decisions, we would expect subjects to set their threshold higher than the optimal amount.

5.5.5 Cognitive Ability

For a subset of our subjects we have a measure of cognitive ability. We find a range of performance on this task: 19% of subjects got zero questions correct, while 36% got all three correct. The average score was 1.79 correct. We include the CRT score as a measure of cognitive ability in

[17] For all results in Table 6 we find very similar results if we instead use the difference between the actual answer policy and the optimal static threshold with adjustments policy.

Table 6: Alternate Explanations for Deviations

VARIABLES	(1)	(2)	(3)	(4)	(5)
# Periods Left	0.00783***	0.00784***	0.00785***	0.00784***	0.00957***
	(0.000970)	(0.000970)	(0.000970)	(0.000970)	(0.00121)
10 Calls Treatment & 0 Calls Left	0.404	-0.0714	-0.0176	-0.161	0.351
	(0.533)	(0.157)	(0.161)	(0.158)	(0.434)
20 Calls Treatment & 0 Calls Left	-0.276	-0.421**	-0.177	-0.363	-0.215
	(0.714)	(0.196)	(0.207)	(0.223)	(0.589)
10 Calls Treatment & 1+ Calls Left	0.974*	0.498***	0.552***	0.408**	0.896**
	(0.537)	(0.164)	(0.169)	(0.166)	(0.466)
20 Calls Treatment & 1+ Calls Left	0.382	0.236	0.480**	0.295	0.466
	(0.716)	(0.194)	(0.205)	(0.221)	(0.585)
Risk Aversion & 0 Calls Treatment	0.0446				
	(0.0714)				
Risk Aversion & 10 Calls Treatment	-0.0421				
	(0.0491)				
Risk Aversion & 20 Calls Treatment	0.0284				
	(0.0896)				
Regret Averse & 0 Calls Treatment		-0.605	0.309		
		(0.480)	(0.216)		
Regret Averse & 10 Calls Treatment		-0.319	0.103		
		(0.297)	(0.340)		
Regret Averse & 20 Calls Treatment		0.251	-0.499		
		(0.554)	(0.467)		
Sunk Cost Fallacy & 0 Calls Treatment				-0.203	
				(0.279)	
Sunk Cost Fallacy & 10 Calls Treatment				0.117	
				(0.302)	
Sunk Cost Fallacy & 20 Calls Treatment				-0.0678	
				(0.360)	
CRT Score & 0 Calls Treatment					0.214***
					(0.0811)
CRT Score & 10 Calls Treatment					-0.118
					(0.160)
CRT Score & 20 Calls Treatment					0.0551
					(0.252)
Task Controls	YES	YES	YES	YES	YES
Constant	-0.327	-0.0433	-0.171	-0.0399	-0.517**
	(0.441)	(0.103)	(0.117)	(0.105)	(0.203)
Observations	9681	9681	9681	9681	5388
Number of Subjects	100	100	100	100	57

Robust standard errors reported in parentheses. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The dependent variable is the difference between the subject's answer threshold and the optimal threshold. The specification is OLS subject random effects, and the observations are restricted to periods where the subject used a threshold policy. The constant term reflects the policy in the omitted 0 Calls treatment. Column 2 uses the lottery measure of regret aversion, while Column 3 uses the ultimatum game measure.

Column 5 of Table 6. Cognitive ability has no significant effect on choice in the 10 and 20 Calls treatment, however subjects with lower CRT scores are significantly more conservative (and in fact too conservative) in the 0 Calls treatment. This is somewhat puzzling, since the 0 Calls treatment is a much simpler consumption problem. However, since the CRT measures the subjects' depth of thinking it may be proxying for boredom and impatience with the task, rather than calculating ability.

6 Experiment 2

We conducted a second experiment that replicates the first experiment, but provides subjects with the exact distribution of call values (instead of having them draw sample outcomes from the distribution). While this is arguably less realistic than the experience-based design of our main experiment, providing a complete description allows us to test whether our results are an artifact of giving subjects only incomplete information about the value distribution. A total of 36 students participated, with 18 each in the 0 Calls and 10 Calls treatment.

6.1 Results

Figure 5 displays the answer rates for each type of call in each treatment. Subjects' decisions are largely similar to our previous results, including a substantial increase in the answer rate of the \$0.30 and \$0.15 calls when subjects have free calls. One difference is that subjects answer the \$0.45 call only 64% of the time with free calls, which is lower than in Experiment 1. We also find that subjects consistently use threshold policies, as in Experiment 1: 87% of decisions in the 0 Calls treatment, and 96% of decisions in the 10 Calls treatment are threshold policies.

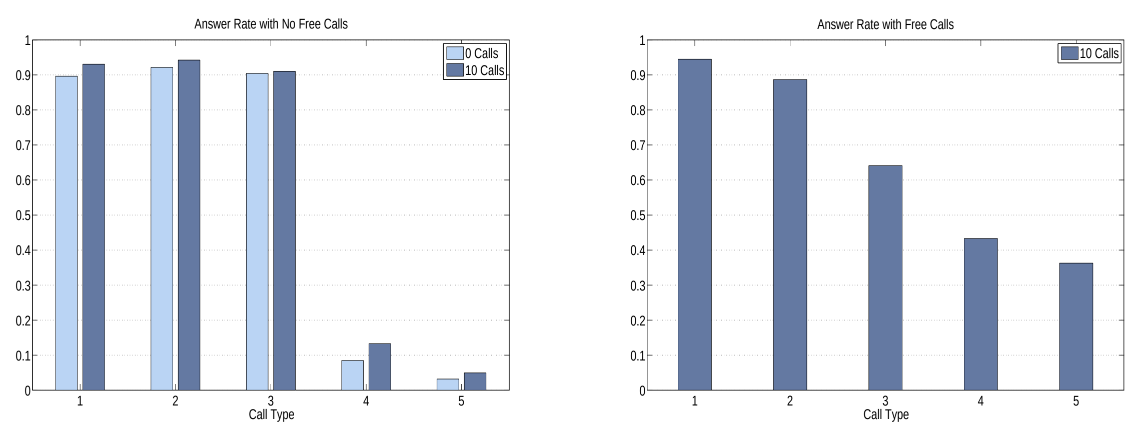


Figure 5: Answer Rates with and without Free Calls

Subjects is this experiment have significantly more accurate beliefs than subjects in our previous experiment. Subjects overestimate the number of 0.75 calls by 0.66 on average (compared to 0.99 in the Experiment 1, ranksum test $p < 0.01$), and overestimate the number of 0.15 calls by 1.03 on average (compared to 2.23 in the Experiment 1, ranksum test $p < 0.01$). Only 22% of guesses overestimate the number of high value calls by at least 1 (compared to 35%, test of proportions $p < 0.01$), and only 53% overestimate the number of low value calls by at least 1 (compared to 66%, test of proportions $p < 0.01$). It is important to note that these mistakes are likely of a different nature compared to the mistaken beliefs in Experiment 1. Subjects in that experiment were making a mistake of inference and/or memory, while subjects in this experiment have full information, and so are making a mistake of calculation.

To test whether subjects overuse their free calls, we again measure the deviation from the optimal policy as the difference between a subject's answer policy and the optimal policy for each call decision. We then replicated the analysis from Table 5 by regressing the deviation from the optimal policy on treatment controls and mistaken beliefs.[18] As Column 1 demonstrates, we find at least as large an overuse bias for free calls as in the original experiment. This large deviation from the optimal policy remains when we include controls for beliefs. We do find an effect of mistaken beliefs, however the sign of the effect is reversed from our main experiment. Together these results confirm that the overuse bias result is robust to the sampling paradigm. Additionally, they provide further support for our interpretation that mistaken beliefs explain only a part of the overuse bias effect.

7 Experiment 3

We conducted an additional follow-up experiment to measure subjects' willingness to pay for the contracts with free calls (either ten or twenty free calls) instead of having the pay-per-use contract. Procedures were the same as in Experiment 1, except that at the beginning of each task subjects were asked to state the largest "monthly fee" that they would be willing to pay for a 10 Calls contract, or a 20 Calls contract. A random fee was then generated, and the subject was given a contract with 10 Calls (or 20 Calls) and the random fee if their WTP was greater than the fee. If the subject's WTP was smaller than the fee, the subject played the task with the 0

[18] We find very similar results using the difference between the actual policy and the static threshold with adjustments policy.

Table 7: Deviations from Optimal Policy

VARIABLES	(1)	(2)
# Periods Left	0.00582***	0.00590***
	(0.00121)	(0.00122)
10 Calls Treatment & 0 Calls Left	0.747***	0.790***
	(0.0978)	(0.0907)
10 Calls Treatment & 1+ Calls Left	-0.0842	-0.0373
	(0.0868)	(0.0790)
\$0.75 Guess - E[# \$0.75] & 0 Calls Treatment		-0.00896
		(0.0161)
\$0.75 Guess - E[# \$0.75] & 10 Calls Treatment		-0.00494
		(0.00779)
\$0.15 Guess - E[# \$0.15] & 0 Calls Treatment		-0.00239
		(0.0121)
\$0.15 Guess - E[# \$0.15] & 10 Calls Treatment		-0.0738***
		(0.0181)
Task Controls	YES	YES
Constant	-0.283***	-0.257***
	(0.0493)	(0.0440)
Observations	3957	3957
Number of Subjects	36	36

Robust standard errors reported in parentheses. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The dependent variable is the difference between the subject's answer threshold and the optimal threshold. The specification is OLS with subject random effects, and the observations are restricted to periods where the subject used a threshold policy. The constant term reflects the policy in the 0 Calls treatment. Column 2 uses the true expectation of the value distribution.

Calls contract and no fee. We again measured risk aversion the sunk cost fallacy, and cognitive ability.[19] 77 subjects participated in this experiment, with 55 providing WTP for ten free calls, and 22 providing WTP for twenty free calls.

7.1 Results

Consumption behavior is similar to that observed in Experiment 1. In the 10 Calls treatment, subjects answered 18.95 calls on average when they had the 0 Calls contract, and answered 19.91 calls under the 10 Calls contract. Similarly, subjects in the 20 Calls treatment answered 19.91 calls with the 0 Calls contract, and 23.61 calls with the 20 Calls contract. The average value of answered calls is \$0.53 with the 10 Calls contract (compared to \$0.54 in Experiment 1) and \$0.52 with the 20 Calls contract (compared to \$0.52 in Experiment 1).

The mean willingness to pay for ten free calls was \$3.23, with a median of \$3.49. 21% of subjects are willing to pay more than the "face value" of \$3.50, while an additional 29% was willing to pay exactly face value. For twenty free calls the mean willingness to pay was \$6.14, with a median of \$6.50. 8% of subjects were willing to pay more than \$7.00, with another 34% of subjects willing to pay exactly \$7.00. While this is a smaller fraction of subjects "overpaying", note that paying the full pay-per-use price of \$7.00 is a larger mistake for the 20 Calls contract, as the subject loses a substantial option value. Only 51% of subjects received at least twenty high-value calls, whereas every subject received at least ten calls worth paying the per-use cost for. It is particularly noteworthy that willingness to pay actually increases slightly from an average of \$3.14 in the first task to \$3.32 in the fourth for the 10 Calls contract, and increased from \$6.17 to \$6.23 for the 20 Calls contract. Furthermore the percent of subjects willing to overpay increases significantly from 13% in task one to 27% in task four for the 10 Calls contract. In the 20 Calls treatment 5% of subjects were willing to overpay in both the first and fourth periods, with 45% willing to pay at least full price in both periods. This bias towards free units during tariff choice aligns with previous results, and is consistent with consumers anticipating feeling a taxi meter effect during consumption (despite our previous results indicating that a taxi meter effect does not affect consumption behavior).

Table 8 reports the results of regressing subjects' willingness to pay on various individual characteristics. While we have previously shown that mistaken beliefs significantly influence consumption

[19] The two regret aversion measures were eliminated to keep the session length approximately the same.

Table 8: Willingness to Pay

	10 Calls Treatment				20 Calls Treatment			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$0.75 Guess - E[# $0.75]	0.0368				-0.0336			
	(0.0269)				(0.0541)			
$0.15 Guess - E[# $0.15]	0.000489				0.0294			
	(0.0261)				(0.0653)			
Risk Aversion		-0.0584				-0.223		
		(0.0460)				(0.162)		
Sunk Cost			0.106				0.756*	
			(0.168)				(0.425)	
CRT Score				-0.00942				0.0572
				(0.0850)				(0.302)
Task Controls	YES	YES	YES	YES	YES	YES	YES	YES
Constant	3.051***	3.480***	3.101***	3.151***	6.114***	7.367***	6.067***	6.059***
	(0.112)	(0.284)	(0.136)	(0.199)	(0.288)	(0.858)	(0.312)	(0.755)
Observations	220	220	220	220	88	88	88	88
Number of Subjects	55	55	55	55	22	22	22	22

Robust standard errors reported in parentheses. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The dependent variable is the subject's willingness to pay for ten (twenty) free calls. The specification includes subject random effects.

decisions, they do not appear to affect subjects' willingness to pay for free units of access. This is useful from the firm's perspective, since the kind of mistaken beliefs that lead to overuse of free calls that the individual is endowed with could potentially reduce their willingness to pay ex ante for free calls if individuals use these beliefs in evaluating potential contracts. However, it appears that the decision process to select a contract does not rely upon beliefs in the same way as the decision process to use a contract. We also again find largely no effect of other behavioral factors such as risk aversion, the sunk cost fallacy and cognitive ability, although there is a marginally significant increase in WTP for 20 Calls among subjects who exhibit the sunk cost fallacy.

We do find that some aspects of contract choice affects subjects' consumption patterns. Table 9 reports the results of regressing the number of calls a subject answered on the randomly generated monthly fee (odd columns) or the subject's willingness to pay (even columns). We report observations for the 0 Calls contract and the 10 Calls contract for the 10 Calls treatment in columns 1-2 and columns 3-4, respectively, and the 0 Calls and 20 Calls contract for the 20 Calls treatment in colums 5-6 and 7-8. Neither the price paid, nor the subjects' willingness to pay appear to affect consumption under either the 10 Calls or 20 Calls contracts. However, subjects in the 10 Calls treatment with a 0 Calls contract who faced a high fee for the 10 Calls contract answer significantly fewer calls than those who faced a lower fee. While a portion of the effect could be driven by the mere exposure to the price, it appears that this effect can substantially be explained by a sorting effect: subjects with a higher willingness to pay for free calls consume significantly fewer calls under a pay-for-use contract (i.e. this subset of subjects exhibit a taxi meter effect on consumption). Therefore, pre-selling access units can have three beneficial effects for the firm: it extracts revenue from high-value consumers, it leads to increased usage of the service, and it screens out from the pay-per-use contract those customers who are least profitable under that contract. We did not, however, find an analogous sorting effect in the 20 Calls treatment, so the screening benefit may depend on the menu of contracts that the firm offers.

7.1.1 Optimal Pricing

Given the observed distribution of consumer willingness to pay, and the estimated effects of price on behavior, we can identify the revenue maximizing fee for the 10 Calls contract. Based on our data for the willingness to pay for the 10 Calls contract the optimal fee is \$3.49 - a very small discount relative to the per-call price. This leads to an average revenue of \$6.97 per customer, a 15.4% increase over the estimated average revenue of \$6.04 if the firm does not offer a presale

Table 9: Consumption and Willingness to Pay

	10 Calls Treatment				20 Calls Treatment			
	0 Calls Contract		10 Calls Contract		0 Calls Contract		20 Calls Contract	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Random Fee	-1.333**		0.184		-0.151		-0.230	
	(0.620)		(0.340)		(0.278)		(0.204)	
WTP		-0.882*		0.183		0.0447		0.152
		(0.524)		(0.566)		(0.274)		(0.370)
Constant	23.93***	21.33***	19.57***	19.26***	20.94***	19.52***	24.46***	22.75***
	(2.368)	(1.567)	(0.716)	(1.878)	(2.050)	(1.560)	(0.741)	(2.382)
Observations	81	81	139	139	34	34	54	54
Number of Subjects	47	47	55	55	19	19	21	21

Robust standard errors reported in parentheses. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The dependent variable is the total number of calls answered. The specification is OLS with subject random effects.

contract. Any price between \$2.85 and \$4.00 would lead to a revenue increase of up to 10%, and any price above \$2.18 would increase revenue over not preselling. Because the WTP distribution shifts slightly, we also examine the optimal price given the WTP distribution from task 4. We again find that \$3.49 is the optimal price, with an estimated increase in revenue of 15.9%. If we use the consumption-WTP relationship instead of the consumption-price relationship, we also find that the optimal price of \$3.49.

If we do not include the effect of price (or WTP) on consumption under the 0 Calls contract in the 10 Calls treatment, we still find the correct price, but would overestimate the potential revenue from not pre-selling. Under this model preselling units would appear to only increase revenue by 4.3%. It is therefore important to properly account for the effect of the menu of contracts on resulting consumption behavior, as this misestimate of the benefits of preselling could adversely affect firm decisions.

We can similarly find the optimal fee for the 20 Calls contract given our data. As before we find that the optimal price is \$6.95 - a very small discount relative the pay-per-use contract.[20] This fee leads to an average revenue of \$7.54, a 8.3% increase over the estimated revenue of &6.97 if the firm only offers the pay per use contract. Any price between \$6.39 and \$7.00 would lead to

[20]To calculate the optimal price for the 20 Calls contract we do not include an effect of WTP on consumption under the 0 Calls contract, as there was no significant effect observed in the 20 Calls treatment.

an increase in revenue of at least 5%, while any price of at least \$6.00 would increase revenue at least some amount. If we use the WTP distribution from task 4, we again find that \$6.95 is the optimal price, with an estimated increase in revenues of 8.9%.

8 Discussion and Concluding Remarks

In this paper we present a plausible decision heuristic (the static threshold with adjustments policy) that consumers may use consuming access services. A simple static threshold with adjustments policy that accounts for the number of remaining free units and the amount of time left before the expiration of the contract can lead to expected consumption utility that is close to the optimal dynamic policy. We also consider how various decision biases (such as mistaken beliefs about the value distribution, risk aversion, the sunk cost fallacy and the taxi meter effect) could affect consumption decisions.

We then test our model using a dynamic consumption experiment modeled on cell phone services. We find that a majority of subjects use a threshold policy in making consumption decisions, with choices matching the static threshold in many cases. However, subjects use free calls too quickly, leading to average payoffs significantly below the expected benefit under the optimal policy. Many subjects exhibit behavioral biases that significantly affect behavior: subjects who underestimate the upper tail of the value distribution or who overestimate the lower tail use free units more liberally. Furthermore, these mistakes persist throughout the experiment. We also measure subjects' willingness to pay for free calls, and find that a substantial number are willing to overpay. This leads to the optimal price involving only a very small discount, and that offering the optimal three part tariff contract increases revenue by approximately 8 to 15%.

In our study, we find support for results of Ascarza, Lambrecht, and Vilcassim (2009). They indicate that the satiation level of individuals on a three part tariff is on average 31.5% greater than on a two part tariff. We also find subjects over-use minutes when they are on a three part tariff compared to their usage when they are on a pay-per-use contract. However, Ascarza et. al do not model the dynamics of consumer decision making or test possible explanations for overuse. They explain overuse by the additional utility that individuals may obtain from three part tariffs since three part tariffs may result in greater enjoyment in usage.

Grubb and Osborne (2011) have estimated a structural model of contract choice and usage in cellular-phone services on a data set of individual cellular phone bills. Their paper is very interesting, and shares some of the same insights as our experiment. However, our results suggest caution in making some of structural assumptions of Grubb and Osborne. On the positive side, we find some supportive evidence for the "inattentive consumption threshold" assumption when our subjects have free calls. This result disappears when subjects run out of free minutes, but note that subjects in our experiment could easily tell when they ran out of free minutes, while this may not be as easy for individuals in their data. On the other hand, we do find that subjects adjust their threshold when they have many free calls left near the end of the period, and we do not find that individuals make optimal consumption decisions given their beliefs, nor do we find that individuals learn in a sophisticated fashion. Instead we find that subjects overconsume beyond what their beliefs justify, and that both mistaken beliefs and overconsumption persist over time.

One important implication of our results for the broader literature is to caution against the common assumption that the same biases drive both tariff choice and consumption decisions. While it is a natural assumption that the same decision process that determines how much a consumer values access units *ex ante* also determines how the consumer uses them, our results suggest that this need not be the case. In our experiment there is only a weak connection between a consumer's willingness to pay for free calls, and the subsequent consumption decisions. Moreover, the effect of biased beliefs about the value distribution that partially explains consumption behavior plays no role in determining willingness to pay. Thus, it seems there are two distinct decision processes that consumers choices: one for tariff selection and another for consumption. This may be particularly important for empirical research, where researchers typically must make strong identifying assumptions about consumers' decisions processes to address consumer heterogeneity and selection, as well as the inability to observer consumer value distributions, beliefs, etc.

Finally, some of the earlier literature suggests hyperbolic discounting as the potential source of over-usage of services (Yao et. al. 2011). Our experiment cannot speak directly to this mechanism, as all consumption decisions occur within a short span of time. While it is likely that hyperbolic discounting is indeed a contributing factor to many observed examples of overconsumption behavior, it is of note that we still find significant over-usage when subjects have free minutes in setting that rules out hyperbolic discounting.

While our current experiment is focused on the consumption decisions given a specific contract, two natural extensions are to examine further how consumers may choose between potential contracts given these consumption biases, and how firms should respond to these biases in consumption behavior in choosing what contracts to offer and how to price the contracts in order to maximize profit.

9 Appendix

In all the proofs for notational simplicity we assume V has continuous support.

Proof of Theorem 2: Suppose $t\bar{F}(q) < k$, then $J^s(k,t,q) = E(V|V > q)t\bar{F}(q)$ which is decreasing in q, so $q^* \leq q(k,t)$. Now consider the case $t\bar{F}(q) \geq k$. The first order derivative with respect to q is $\frac{\partial J^s(k,t,q)}{\partial q} = \frac{\partial}{\partial q}\left[k\frac{E(V-q)^+ - E(V-p)^+}{\bar{F}(q)} + kq\right] \geq 0$ which implies J^s is increasing in q. Therefore, $q^* = \min(q(k,t),p)$.

Proof of Theorem 3: If $q(c,T) < p$ then $u(c,T,p) = TE(V - q(c,T))^+ + cq(c,T)$ and the derivative with respect to T is $E(V - q(c,T))^+ \geq 0$, the derivative with respect to c is $q(c,T)$. On the other hand, if $q(c,T,p) = p$ then the derivative with respect to T is $E(V-p)^+$, the derivative with respect to c is p. We can summarize by writing $\frac{\partial u(c,T,p)}{\partial} = E(V - q(c,T,p))^+$, $\frac{\partial u(c,T,p)}{\partial c} = q(c,T,p)$, and $\frac{\partial u(c,T,p)}{\partial p} = -1(q(c,T) > p)pf(p)$.

The monotonicity of $u(c,T,p)$ in c and T follows from $\frac{\partial u(c,T,p)}{\partial c} = q(c,T,p) \geq 0$ and $\frac{\partial u(c,T,p)}{\partial T} = E(V - q(c,T,p))^+ \geq 0$. Moreover, notice that $\frac{\partial^2 u(c,T,p)}{\partial c^2} = -\frac{1}{f(q(c,T,p))}$, $\frac{\partial^2 u(c,T,p)}{\partial (T)^2} = -\frac{c}{^2h(q(c,T,p))}$, $\frac{\partial^2 u(c,T,p)}{\partial c \partial T} = \frac{1}{h(q(c,,p))}$, so $\frac{\partial^2 u(c,T,p)}{\partial c^2}\frac{\partial^2 u(c,T,p)}{\partial^2} - \frac{\partial^2 u(c,T,p)}{\partial c \partial}^2 = 0$. Therefore, $u(c,T,p)$ is jointly concave in (c,T) for fixed p.

Proof of Theorem 4: If $V \succeq W$ then $\bar{F}_V(y) \geq \bar{F}_W(y)$ for all $y \geq 0$. Therefore, $q_V(c,T) \leq q_W(c,T)$ by the definition of $q(c,T)$.

Proof of Theorem 5: Suppose that $U(y) = \frac{y^{1-r}}{1-r}$ and the risk averse utility from the consumption of the service $\min(T\bar{F}(q),c)E(U(V|V > q)) + (T - \frac{c}{\bar{F}(q)})^+E(U((V-p)^+)) - x$. If $T > c$, taking the derivative we obtain $cE\left(\frac{\partial U(V|V>q)}{\partial q}\right) + cf(q)\frac{E(U((V-p)^+))}{\bar{F}(q)^2}$. Since $U(V|V > q)$ is increasing in q, the derivative is non-negative. Therefore, the optimal threshold is greater or equal to $q(c,T)$. If $T\bar{F}(q) \leq c$, taking the derivative of the utility with respect to q we obtain $Tf(q)E(U(V|V > q)) + T\bar{F}(q)E\left(\frac{\partial U(V|V>q)}{\partial q}\right)$. This can be positive or negative, therefore it is possible to have a threshold that is strictly higher than $q(c,T)$ with risk averse utility functions.

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