Contracts, Biases and Consumption of Access Services

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We study theoretically and empirically the consumption of access services. We demonstrate that consumption is affected by contract structure (pay-per-use vs. three part tariffs) even if the optimal consumption plans are identical. We find that, while there is extensive individual heterogeneity, on average consumers' choices follow a structure that is similar to a nearly optimal heuristic and correctly react to imbalances between the number of free calls and call opportunities remaining. 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. In response, the optimal firm strategy offers a three-part tariff at a very small discount, which increases revenue by $8-14\%$ compared to only offering a pay-per-use contract.

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.

When choosing an access contract 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. In this paper, we investigate how different contractual forms (pay-per-use or three part tariff) 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. In addition to these two dynamic policies, we consider a myopic and a static heuristic that were studied in the existing literature. 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 contract that provides 0, 10 or 20 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). To study how the structure of subjects' decisions compare to the four policies we consider, we first ask which policy structures are more consistent with the aggregate patterns in individual choices. We also explore individual heterogeneity and match each individual's profile of choices to the four policies. Additionally, we examine within the structure of subjects' choices whether they are correctly "calibrated" in the sense of using their allotment of free calls at the optimal rate.

When we study the aggregate patterns in consumer choice, both the optimal dynamic policy and the proposed nearly optimal dynamic heuristic describe the average structure of subjects' choices well, with subjects adjusting 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 average 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. When we explore the individual profiles, we find that a substantial fraction of subjects consistently use the static and myopic policies and an equally high fraction are consistently using dynamic policies. When the policies are distinguishable, our proposed dynamic heuristic provides the best unique description of the subject decisions among myopic, static, optimal dynamic and heuristic dynamic policies. Overall, we find that many subjects are reasonably sophisticated, in that they use dynamic choice rules that follow the patterns of the optimal dynamic policy, however they consistently exhibit an overuse bias. Therefore on average consumers can best be thought of as moderately sophisticated - neither being fully myopic nor fully optimal.

Additionally, we measure subjects' beliefs about the value distribution, and show that mistaken beliefs can explain part of the overusage effect. Specifically, subjects with a contract providing 20 free calls who overestimate the frequency of low value calls (and therefore underestimate the value of future calls) are more liberal in using their free calls. However, mistaken beliefs do not lead to overusage in the 10 Calls treatment. 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 treatment the subjects who report the highest willingness to pay for free calls also 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: extracting revenue via the monthly fee from consumers who value free calls highly, sorting consumers out of pay-per-use that will be low usage customers, and increasing the usage of consumers with free calls. We do not find a similar sorting effect in the 20 Calls 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 14% 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 10 Calls contract increases firm revenue more than the 20 Calls contract due to both greater overvaluation of the contract and greater revenue generated from consumer overusage of free calls.

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 uncertainty about future demand and consumption valuations. Instead, the consumer must rely on an estimate over her usage during the contract duration. 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. Behavioral research on optimal stopping problems such as when to stop job search, or when to adopt a new technology is also related to this work. Majority of this research is in the context of labor economics (Cox and Oaxaca (1989), Schotter and Braunstein (1981)) and the decision maker has a single position to fill (single unit to consume). They show that decision makers employ complex but sub-optimal policies that are structurally similar to the optimal. Bearden, Murphy, Rapoport (2007) study the closest optimal control problem (a standard revenue management problem where the seller maximizes his revenue from multiple units over a finite horizon by accepting and rejecting the offers for multiple units that arrive sequentially over time) to ours. Different than Bearden et. al., we directly elicit the strategy of the consumer before each decision which allows us to identify the consumer's policy more clearly. Moreover, we theoretically show how behavioral biases would change the optimal and heuristics policies as well as perform several diagnostic tasks to identify the behavioral biases in decision making.

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, Grubb 2005). In particular, 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 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 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, K, p) where x is the access fee, K is the number of free units (initial allowance), p is the non-negative per unit fee for any consumption over initial allowance. The consumer pays fixed cost x for the right to use the service and K free units in T periods. If her consumption turns out to be more than K, 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 theoretically study the contract purchase decisions and the optimal menu of contracts.

Consumers are uncertain about their exact consumption levels and the value of each consumption opportunity, 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. 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. Stochastic Dynamic Consumption Model and Optimal Policy

Most individuals use shortcuts and heuristics when making daily consumption decisions. To understand the consumption problem and identify plausible heuristics, we first solve the discrete time optimal control problem of an unboundedly rational consumer who holds an (x, K, p) contract with a duration of T periods. Then we derive heuristics that have similar structural properties with this dynamic optimal policy.

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. Each consumption uses one unit of service. With k units left and t periods to go, the optimal expected utility is given by

$$J(k,t) = E[\max\{V + J(k-1,t-1), J(k,t-1)\}], \quad k > 0, t \geq 1$$

$$J(k,t) = tE(V-p)^+ \quad k \leq 0, t \geq 0.$$

If there are t periods to go until the contract coverage ends, the consumer observes the value of the service and decides whether to use the service or not. If a free unit is used, then her 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 her 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 the value of the consumption opportunity is greater than the pay per unit fee, $V \geq p$, resulting in the expected utility $tE(V-p)^+$. With some algebra we can write the optimal expected utility as $J(k,t) = J(k,t-1) + E[\max\{V - \Delta J(k,t-1), 0\}]$ 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 a threshold policy to ration the consumption opportunities, and characterizes the optimal *stochastic dynamic threshold* (SDT). She uses the service if the value of the service is greater than the threshold $\Delta J(k,t)$. $\Delta J(k,t)$ is the opportunity cost of using the kth remaining free unit when there are t periods to go. The threshold, $\Delta J(k,t)$, is a function of the valuation distribution V, pay-per-unit fee, the number of remaining free units, and remaining time until contract expires.

THEOREM 1. *(Stochastic Dynamic Threshold Policy)*[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.*

[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.

The first part of Theorem 1 states that the consumer utility is higher if she has more free units and more time to use the free units. The last two parts show that the threshold is decreasing in the number of free units, increasing in the remaining time t and per unit price p. This implies that the consumer becomes more conservative in her usage as the remaining time in her contract and the pay-per-unit fee increase, while she becomes more liberal in her usage as the number of free units in the contract increases.

Although a rational individual who has infinite computational ability would use the optimal stochastic dynamic threshold policy stated in Theorem 1, it is more likely that she uses a heuristic in making consumption decisions as computing and updating the optimal threshold over time requires solving a non-trivial stochastic optimization problem. Next we will use our understanding of the structure of the optimal policy to develop near optimal dynamic heuristics. We discuss three heuristics some of which are proposed by the earlier literature in the following section.

3.2. Heuristic Policies

In this section we study three heuristic policies in increasing complexity: i) a myopic policy, ii) a deterministic static threshold policy (DST) and iii) a deterministic dynamic threshold policy (DDT). The myopic and a version of the static policy are previously studied by Liebman and Zeckhauser (2004), and Borenstein (2009) respectively. Here we show the connection of the deterministic static threshold policy to the optimal policy, and then we propose an alternative to this totally static (inattentive) heuristic, the deterministic dynamic threshold policy. This alternative decision rule is structurally similar to the optimal policy but easier to compute and results in higher consumer surplus than myopic and deterministic static policies as it updates the policy over time (hence it is a deterministic but attentive policy). In Section 5 we investigate which of the three heuristic policies and the stochastic optimal policy match consumption decisions better in a cell phone usage experiment.

Myopic Policy: With the myopic policy, also called 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 on the remaining decisions (i.e. they ignore the opportunity cost of the current decision). Thus consumers with an (x, K, p) contract will use a free unit for any consumption opportunity that has a positive value (i.e. use threshold zero to filter the consumption opportunities) if they have free units and will use a unit if the value of the consumption opportunity is greater than the per unit cost p if there are no free units left (i.e. use p as the threshold when they run out of free units). This policy ignores the opportunity cost of using a free unit now and the possibility of seeing higher valued consumption opportunities in the future.

Deterministic Static Threshold Policy: The stochastic static threshold policy, first proposed by Borenstein (2009) and 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 deterministic static heuristic policy that is asymptotically optimal for the stochastic optimal control problem stated in Section 3.1 as the free units in the contract and the number of consumption opportunities grow. The threshold is static because it is calculated only once at the beginning of the contract duration and deterministic in the sense that it ignores the uncertainty in the number of future consumption opportunities and assumes the number of opportunities is known (in expectation).[3] During the course of the contract, the consumer is inattentive and does not track usage but simply makes all calls valued above the threshold.[4]

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 stated in 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 $E(V|V>q)$. 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:

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

We assume here the consumption opportunities arise in every period and therefore the number of answered calls, D_q, is a Binomial random variable with parameters t and $\bar{F}(q)$. This optimization problem is still a non-trivial stochastic optimization problem[5]. To simplify the heuristic even further we assume that the consumer considers only the expectation of the number of units consumed if threshold q is used (i.e., ignores the fact that D_q is a Binomial random variable with parameters t and $\bar{F}(q) = P(V \ge q)$, and assumes that the total number of consumption opportunities filtered with q is equal to the expectation of D_q, $t\bar{F}(q)$). Replacing stochastic demand D_q with its expectation,

[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.

[3] Note that in our experiment the number of call opportunities is fixed and known to our subjects.

[4] The customer is attentive to no longer having any free calls, and will adjust her policy in this case.

[5] Solutions to structurally similar problems are given in Borenstein (2009) and Grubb and Osborne (2011)

we obtain the following *deterministic* approximation [6] to the consumer utility problem which we use to derive the DST:

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

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. Notice that deterministic approximation $J^d(k,t)$ provides an upper bound on the utility given by the stochastic problem[7]. We call the policy derived from this problem the *deterministic static threshold policy*. We define $q(k,t) = \min\left\{q \ge 0 | P(V>q) \le \frac{k}{t}\right\}$ as the free-unit clearing threshold. Notice that q can not be larger than the per unit price p, so we have $q(k,t,p) = \min\{p, q(k,t)\}$.

Theorem 2. *i) $q(k,t,p)$ maximizes $J^d(k,t,q)$, ii) $q(k,t,p)$ is decreasing k and increasing in t, iii) $J^d(k,t)$ is increasing and jointly concave in k and t for any fixed p, iv) $J^d(k,t)$ is decreasing in p for any fixed (k,t).*

Theorem 2 shows that free-unit clearing threshold bounded by pay per unit fee maximizes the deterministic approximation $J^d(k,t,q)$. Given a contract (x,K,p) to be used in T periods, we define the deterministic static threshold as $q^{DST}(k,t,p) = q(K,T,p)$ for any $k \le K$ and $t \le T$. This quantity is calculated at the beginning of the contract duration and is not updated. Notice that DST mimics the structure of the stochastic dynamic optimal policy (Theorem 1) while it is significantly easier to calculate compared to both the stochastic optimal dynamic threshold policy and the stochastic static threshold policy (the optimal solution of $J^s(k,t,q)$). It requires a simple comparison of the ratio of the expected number of consumption opportunities to the number of free units (k/t) with the likelihood of receiving a call that has value greater than q^{DST}. This suggests that the individual should answer the top $100k/t$ percent of the highest valued calls. As the expiration time T decreases, expected number of consumption opportunities decreases, therefore the consumer chooses a lower threshold at the beginning of the horizon and uses the free units more liberally. If the contract has fewer number of free units, the consumer chooses a higher threshold (use the free units more conservatively). One can also show that this deterministic static heuristic is asymptotically optimal (as T and K increases) for the stochastic optimal control problem discussed above.

[6] Savage (2012) calls this type of deterministic approximations of stochastic variables the 'flaw of averages' and discusses extensively when they are good approximations.

[7] We can see that the deterministic utility is an upper bound to the stochastic utility by realizing $\min(D_q,k) = D_q - (D_q-k)^+$, $E(V|V>q) - \frac{E(V-p)^+}{\bar{F}(q)} \ge 0$ for $q \le p$ and using the Jensen's inequality for convex functions: $J^s(k,t,q) = E(V|V>q)(ED_q - E(D_q-k)^+) + E(V-p)^+\frac{E(D_q-k)^+}{\bar{F}(q)} = E(V|V>q)E(D_q) - E(D_q-k)^+\left(E(V|V>q) - \frac{E(V-p)^+}{\bar{F}(q)}\right) \le E(V|V>q)t\bar{F}(q) - (t\bar{F}(q)-k)^+\left(E(V|V>q) - \frac{E(V-p)^+}{\bar{F}(q)}\right) = J^d(k,t,q)$.

Deterministic Dynamic Threshold Policy: This heuristic builds upon the analysis and discussion of the static threshold policy. While the stochastic optimal dynamic threshold policy assumes completely attentive and sophisticated decision makers, the deterministic static threshold policy lies on the other end of the spectrum by assuming inattentive decision makers (they do not change their behavior in response to the fact that opportunity cost of using each free unit changes over time). We expect decision makers to adjust their behavior over time as they use up their free units. The question is how they can adjust their behavior in a computationally inexpensive way. As we discuss above, DST requires a simple computation which can be easily repeated without increasing the computational burden on the decision maker or require higher analytical sophistication. Therefore, we consider the dynamic version of the deterministic heuristic discussed above. Consumers who use the deterministic dynamic threshold policy re-solve $J^d(k,t,p)$ at every consumption opportunity and re-calculate the deterministic static threshold $q(k,t,p)$ that would apply for the remaining time. Given a contract (x,K,p), consumer uses the threshold $q^{DDP}(K,T,p)=q(K,T,p)$ at the beginning of the horizon, but updates this threshold to $q^{DDP}(k,t,p)=q(k,t,p)$ as the free units used $(k<K)$ and the remaining time in the contract decreases $(t<T)$. 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 the affect of possible future adjustments on the current policy while adjusting the current threshold. This increases the expected utility and partially captures the dynamic nature of the optimal policy.

Next we study how behavioral biases alter the heuristic policies.

3.3. Over(Under) Estimation of Call Value Frequency and Overconfidence

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 shows how the optimal and the deterministic static thresholds of a consumer who over (under) estimates demand or the valuation distribution differs from a rational consumer's threshold.

Theorem 3. *Suppose that V is the true valuation distribution and W is the consumer's perception of her valuation distribution. If V first order stochastically dominates W, $V \succeq W$, then $\Delta J_V(k,t) \geq \Delta J_W(k,t)$ and $q_V^{DDT}(k,t,p) \geq q_W^{DDT}(k,t,p)$.*

If the consumer estimates the upper tail of the valuation distribution to be lighter (heavier) than it really is, then she is more aggressive (conservative) in using free units than she is if her estimates are correct with the optimal policy, deterministic static policy and dynamic deterministic policy[8].

[8] As DST is a special case of DDT with $(k=K, t=T)$, we only state the theorem for the DDT.

Over(under) estimation of the upper tail results in lower consumer surplus than consumers would obtain if they use 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 importance 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 (for example, 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.

THEOREM 4. 1. *Suppose that* $U(y) = -e^{-\gamma y}$ *with* $\gamma \geq 0$ *for* $y \geq 0$. *A consumer with higher risk aversion uses a lower optimal threshold for any* k *and* t, $\Delta J_{\gamma_1}(k,t) \leq \Delta_{\gamma_2} J(k,t)$ *for* $\gamma_1 \geq \gamma_2$.

2. *Suppose that* $U(y)$ *is increasing and concave for* $y \geq 0$. *A consumer with higher risk aversion uses a lower optimal threshold than a risk neutral individual:* $q_{RA}^{DDT}(k,t,p) \leq q^{DDT}(k,t,p)$.

Theorem 4 states that an individual becomes more liberal in her usage as her risk aversion increases if she uses the optimal policy or a deterministic threshold policy (DST or DDT). Risk aversion has no affect on the myopic policy.

3.5. Sunk Cost and the Taxi Meter Effect

A rational consumer takes 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 deterministic 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 units) 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 $(1+\rho)p$. 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 ($p = 0$).

Table 1 summarizes the theoretical predictions discussed in this Section. Next, we will test these predictions using a cell phone experiment.

Table 1 Summary of Theoretical Predictions

Policy	Threshold at $(k,t),\ k>0$	Static (Inattentive)	Dynamic (Attentive)	Usage with Bias Over-Est.	Risk Aversion	Sunk Cost
Stoch.Dynamic Thresh. (SDT)	$\Delta J(k,t)$	No	Yes	Conservative	Liberal	Liberal
Myopic	0	Yes	No	No-change	No-change	No-change
Det. Static Thresh. (DST)	$q^{DST} = q(K,T,p)$	Yes	No	Conservative	Liberal	Liberal
Det. Dynamic Thresh. (DDT)	$q^{DDT} = q(k,t,p)$	No	Yes	Conservative	Liberal	Liberal

4. Experiment 1: Design

In order to examine the structure of the consumers' consumption decisions of access services and how the four policies we identified previously relate to their decision rules, 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, regret aversion and the sunk cost fallacy. 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 and independently) for answering the call: \$0.15, \$0.30, \$0.45, \$0.60, or \$0.75.[9] 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.[10] 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.[11]

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. The 10 Calls and 20 Calls treatments allow us to study different aspects of behavior. In the 20 Calls treatment (depending on sequence of call valuations) subjects may face decisions where the optimal SDT and DDT policies differ, while in the 10 Calls treatment the over-usage of free calls is more likely to cause subjects earn a lower payoffs (since on average they should have a lower period of pay-per-use).

Figure 1 displays what the optimal SDT and DDT policies for a given number of free calls left and number of remaining periods for the specific call value distribution used in the experiment[12].

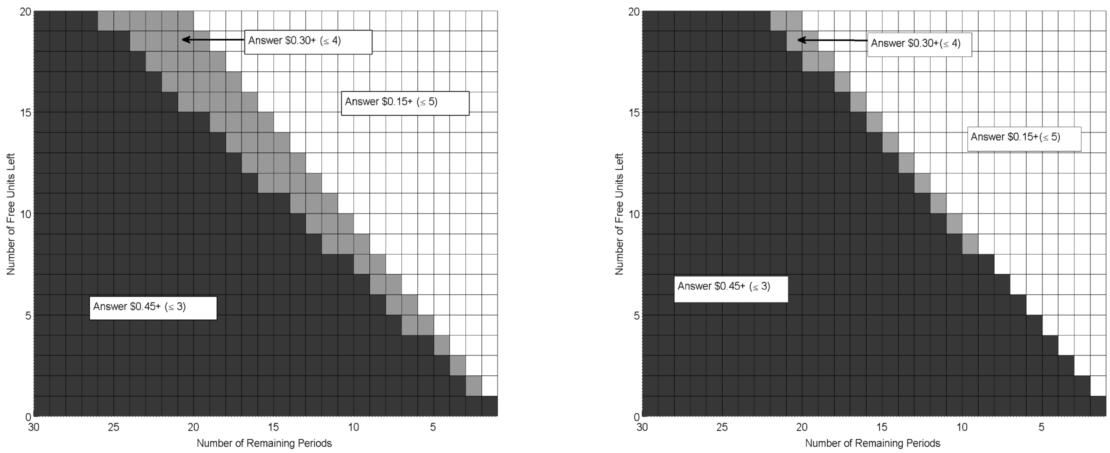
[9] The call values had the following probabilities: $P(\$0.75) = 0.15, P(\$0.60) = 0.25, P(\$0.45) = 0.25, P(\$0.30) = 0.25, P(\$0.15) = 0.10$.

[10] 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.

[11] 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.

[12] We identify the SDT based on the value function described in section 3.1.

The two policies are very similar, with the optimal policy answering the $0.30 call in more cases than the static threshold.



We describe each policy both by the call values answered (e.g. $0.45+) and the call types answered (e.g. ≤ 3).

Figure 1 Stochastic Dynamic Threshold Policy (left) and Deterministic Dynamic Threshold Policy (right)

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.

4.2. 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).[13] 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%

[13] 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.

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 aversion.[14] 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.

[14] 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.[15] Sessions lasted approximately 50 minutes, and subjects earned $12.94 on average.

We will begin by first examining subject decisions for individual calls, then consider the structure of their decision rule throughout the cell phone task (including how such decision rules relate to the four policies we identified previously), and finally we will consider how well calibrated subjects' decision rules are on average, compared to the optimal policy.

5.1. Single Call 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. 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.[16] 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: between 30% and 50% of the time.

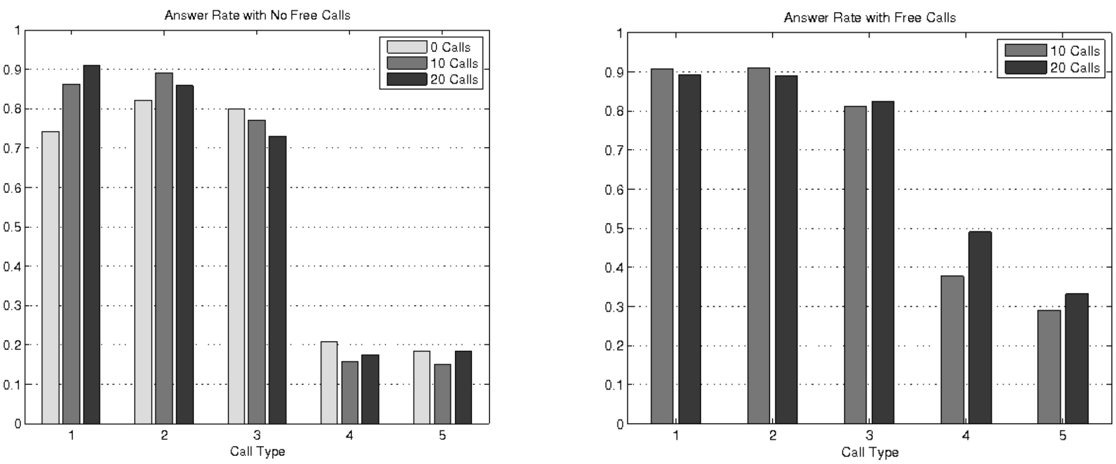
Columns (1) to (5) of Table 2 report the results of regressing subjects' answer policy for each call type on treatment dummies (with and without free calls), task dummies and the number of remaining periods. We include subject random effects, and cluster the standard errors at the subject level.[17] As in Figure 2 there are slight differences between treatments in answering the $0.75 call

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

[16] While the lower answer rate of the $0.75 call in the 0 Calls treatment is a bit surprising, it does not appear to be driven by a few outliers - 35% of subjects choose not to answer the $0.75 call in at least one period. However, this result is not robust - in Experiment 2 subjects in the 0 Calls treatment answer the $0.75 call 90% of the time (see Figure 5), while they answered the two lowest call types in 10% to 20% of decisions.

[17] We do the same for all the regressions reported in this paper.

when the subject has no free calls left. There is no significant difference between treatments for the \$0.60 and \$0.45 calls, however subjects are significantly more likely to answer \$0.30 and \$0.15 when they have free calls remaining.



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

We next examine whether subjects use a threshold policy. Table 3 displays for each treatment the percent of periods in each task where subjects used a threshold policy in an individual period to answer calls[18], as well as the percent of subjects who use a threshold policy throughout the task.[19] 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.[20] 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% (75%) who got three questions correct ($p < 0.01$ for both).

[18] That is, we identify periods where a subject's answer choices are such that the value of every answered call type is higher than the value of every unanswered call type.

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

[20] 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 Experiments 2 and 3 with a 0 Calls contract use a threshold approximately as often as other subjects. In Experiment 3 this is true for the subset of subjects who faced very high random prices (ruling out sorting effects).

Table 2 Answer Policy

	Answer Call Type					Answer Policy	
	\$0.75	\$0.60	\$0.45	\$0.30	\$0.15	(# Types Answered)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
# Periods Left	0.000158	0.00111	0.00160	0.00110	-0.000433	-0.00489	0.00254
	(0.000579)	(0.000735)	(0.00116)	(0.00151)	(0.00140)	(0.00348)	(0.00225)
10 Calls Treatment & 0 Calls Left	0.119	0.0744	-0.0250	-0.0442	-0.0386	-0.180	-0.132
	(0.0781)	(0.0574)	(0.0700)	(0.0720)	(0.0710)	(0.183)	(0.182)
20 Calls Treatment & 0 Calls Left	0.166**	0.0467	-0.0578	-0.0202	-0.00568	-0.301	-0.195
	(0.0767)	(0.0904)	(0.0968)	(0.0732)	(0.0956)	(0.188)	(0.180)
10 Calls Treatment & 1+ Calls Left	0.167**	0.0799	-0.000700	0.165**	0.112	0.594***	0.416*
	(0.0676)	(0.0524)	(0.0698)	(0.0755)	(0.0736)	(0.203)	(0.218)
20 Calls Treatment & 1+ Calls Left	0.150**	0.0667	0.0194	0.281***	0.148**	0.657***	1.031***
	(0.0665)	(0.0549)	(0.0575)	(0.0606)	(0.0660)	(0.175)	(0.186)
10 Calls Treatment: # Calls Left							0.0223*
							(0.0134)
20 Calls Treatment: # Calls Left							-0.0352***
							(0.00885)
Task Controls	YES	YES	YES	YES	YES	YES	YES
Constant	0.695***	0.769***	0.739***	0.193***	0.186***	3.099***	2.982***
	(0.0568)	(0.0438)	(0.0525)	(0.0525)	(0.0533)	(0.143)	(0.139)
Observations	12120	12120	12120	12120	12120	9681	9681
Number of Subjects	101	101	101	101	101	100	100

Standard errors clustered at the subject level reported in parentheses, with columns 1 through 5 estimated jointly as seemingly unrelated regressions. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The dependent variable for columns 1 to 5 is an indicator variable if the subject answered that call type, for columns 6 and 7 it is the subject's answer threshold (i.e. the number of call types answered). The constant term reflects the policy in the 0 Calls treatment. The specification is OLS with subject random effects, and in columns 6 and 7 the observations are restricted to periods where the subject used a threshold policy.

Table 3 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%

Given that most subjects use a threshold policy, we can characterize the five call answer decisions of these subjects by their answer threshold. We will describe an answer policy by the number of call types the subject has chosen to answer. For example, an answer policy equal to 2 means the subject wishes to answer any call worth \$0.60 or more, while an answer policy equal to 5 means the subject wishes to answer all five call types. 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.

In the 0 Calls treatment subjects on average choose a 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.

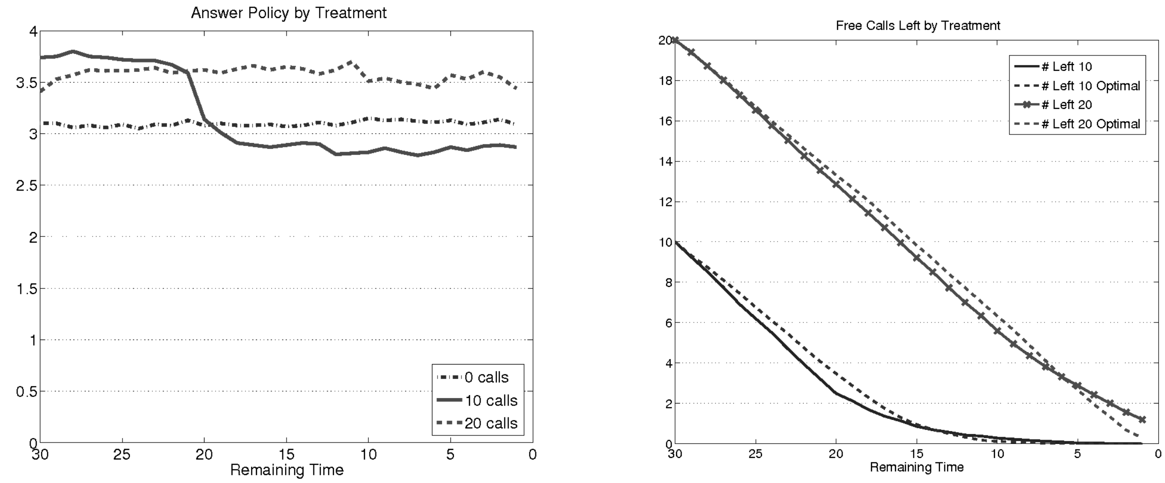


Figure 3 Answer Policy and Free Call Usage

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 (2.96 with zero calls left vs. 3.56 with one or more calls left).

In column (6) of Table 2 we regress the answer policy on the same set of variables as the previous specifications. 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 coefficients for the 10 Calls and 20 Calls treatments are not significantly different ($p = 0.75$). In column (7) we add an additional control for the number of free calls the subject has left. Answer policies are slightly less conservative with more free calls in the 10 Calls treatment, while they are slightly more conservative in the 20 Calls treatment. In both treatments, however, answer policies are significantly higher for any number of free calls than they are with zero free calls. The average answer policy does not differ significantly between the 10 Calls and 20 Calls treatment when subjects have their full allotment of free calls ($p = 0.16$), however they do begin to differ significantly as subjects have relatively few free calls left - the estimated policy with one call left in the 20 Calls treatment is 3.98, compared to 3.42 in the 10 Calls treatment ($p < 0.01$).[21]

[21] These changes in subjects' policies as they run low on free calls does not appear to be driven by differences in the composition of subjects who do and do not reach decision nodes where they have few calls remaining. Every subject

5.2. Decision Rule Structure

We next want to examine what structure exists in the answer choices subjects make throughout a cell phone task - in particular how often, when and why do subjects change their answer choices from one period to the next. Overall, subjects in the 0 Calls treatment change their choices in 11% of periods, while choices change 9% of the time in the 10 Calls treatment and 15% of the time in the 20 Calls treatment. However, part of this is driven by the inconsistent usage of a threshold policy. When a subject uses a threshold policy in two consecutive periods, they only change their policy 1%, 5% and 7% of the time, respectively. For subjects who use a threshold policy in every period of a cell phone task, the average number of policy changes is 0.21 in the 0 Calls treatment, 1.33 in the 10 Calls treatment, and 2.08 in the 20 Calls treatment.

In Table 4 we show the fraction of subjects who use a threshold policy for every period whose profile of answer policies can be characterized into one of several simple forms.[22] Note that very few subjects change their answer policy while they have no free calls (all such subjects are in the "All Others" category). Almost 90% of subjects in the 0 Calls treatment do not change their policy at all - consistent with the optimal policy. For the 10 Calls treatment roughly a third of subjects use a single policy (with 80% of those have an answer policy of 3 throughout), while another third have one policy with free calls and a second without (of those 63% have an answer policy of 5 with free calls and a policy of 3 without, with another 11% have a policy of 4 with free calls and 3 without). In the 20 Calls treatment, only 8% use a single policy, with the two most common policy types have a single change upon using up the last free call (53% have an answer policy of 5 with free calls and a policy of 3 without, and 41% have a policy of 4 with free calls and 3 without), or having multiple changes with free calls (with 73% of these subjects starting with a relatively conservative answer policy - i.e. high threshold - and ending with a more liberal one). Thus most subjects have relatively few policy changes in the 0 and 10 Calls treatment (where we expect few changes based on the optimal policies), while subjects in the 20 Calls treatment tend to change more often.

We can also look at when the policy changes are occurring within the cellphone task. We will focus on the 10 Calls and 20 Calls treatment. 16% of changes occur in the period immediately after

runs out of calls in the 10 Calls treatment. In the 20 Calls treatment 66% of subjects run out, and 90% of subjects end up with three or fewer calls. If we re-run specification (7) only with subjects who end up having three or fewer calls we find essentially the same results (10 Calls Treatment x # Free Calls: $\beta = 0.0241$, $s.e. = .0134$, $p = 0.072$; 20 Calls Treatment x # Free Calls: $\beta = -0.0296$, $s.e. = .00903$, $p = 0.001$). Additionally, if we look within individuals at the change in their average answer policy for their first 3 free calls and their last 3 free calls we find the same results: Subjects in the 10 Calls treatment are significantly less conservative when they have many free calls compared to few (signrank test: $p < 0.001$), while subjects in the 20 Calls treatment are significantly more conservative with many free calls ($p < 0.001$).

[22] For this taxonomy "after last free call" means that change in policy occurs in the period immediately following the use of the last free call.

Table 4 Common Answer Policy Structures

Answer Policy Structure	0 Calls	10 Calls	20 Calls
0 Changes	89.01%	35.29%	8.43%
1 Change, after last free call	0%	34.31%	20.48%
1 Change, w/ free call	0%	4.90%	12.05%
2 Changes, one w/ free calls, one after last free call	0%	1.96%	10.84%
2 Changes, all w/ free calls	0%	0.98%	9.64%
3+ Changes, one after last free call, zero after that	0%	8.82%	6.02%
3+ Changes, all w/ free calls	0%	0%	18.07%
All Others	10.99%	13.73%	14.46%

Includes only subjects who use a threshold policy in all periods.

the subject uses his last free call. While subjects have free calls left, they change their answer policy 21% of the time when the optimal policy changes, compared to 5% when the optimal policy does not change - suggesting subjects are more likely to change in response to the incentives captured in the optimal policy. Furthermore, 37% of the changes that occurred when the optimal policy did not change caused the subject to now match the optimal policy. While subjects have free calls left, they are more likely to change their policy when they did not answer a call last period (10% change without answering a call last period vs. 4% change with answering) - with almost all of those changes to make the policy more liberal (i.e lower the threshold and answer more call types).

5.3. Comparing Decision Rule Structure to the Optimal Policies

Next, we want to consider how the structure of subject's decisions compare to the four policies we discussed in Section 3. We will make this comparison in two levels. First, we will ask which policy structure is most consistent with the aggregate patterns in individual choices. Second, we will explore individual heterogeneity and identify how many individual profiles across all choices can be well-described by each policy .

Aggregate Structure of Choices

First, it is clear from Table 2 that the *myopic heuristic* is not a good descriptor of average behavior across all subjects, since the average answer policy with free calls differs significantly in both treatments from the myopic policy of answering all calls ($p < 0.01$ for both). Table 4 similarly suggests that a *deterministic static policy*[23] does not describe the aggregate patterns of subject choices - 46% of subjects in the 20 Calls treatment (where we expect policy adjustments to occur) use multiple thresholds while they have free calls remaining, and 68% of subjects use multiple thresholds with free calls remaining when they face a call sequence where the stochastic dynamic policy would change[24]. Furthermore, subjects appear to adjust their answer policy in response to the

[23] Note that in our experiment the optimal (i.e. without bias) deterministic static policy is to answer calls of value \$0.45 or higher in every period. We discuss biased versions of our policy types below, however we note here that the biased version of the deterministic static policy (i.e. answer calls of value \$0.30 or higher until running out of free calls) describes only 3% of our subjects in the 10 Calls treatment and 5% of subjects in the 20 Calls treatment.

[24] Similarly, 88% of subjects use multiple thresholds with free calls when the deterministic dynamic policy would change.

underlying incentives captured in either the *stochastic dynamic policy* or the *deterministic dynamic policy*. We can see this further in Table 5 which reports the results of regressing subjects' answer policies on dummy variables for the optimal SDT policy (odd-numbered columns) or the optimal DDT policy (even-numbered columns). In both cases the average policy increases significantly when the optimal policy changes from 3 to 4 or 5 (i.e. the subject has many free calls left relative to the number of remaining periods), even when controlling separately for the number of free calls left. Hence, on average subjects are increasing their answer policy significantly when the optimal DDT and SDT policies indicate they should.[25] Additionally, note that the coefficient on having at least one free call is approximately 0.5, and that the responses to increases in the optimal policy are correspondingly 0.5 smaller than we would expect - this is an initial indication that subjects are (on average) biased towards being to liberal in using their free calls. We analyze this bias in more depth below.

Both of the dynamic policies appear to be good proxies for the overall pattern of subjects' answer policies. Subjects' answer policies match the optimal SDT threshold exactly in 62.4% of decisions, including 41.6% of decisions with 1 or more free calls. Similarly, decisions exactly match the optimal DDT threshold in 63.9% of decisions, including 44.8% of decisions with 1 or more free calls. If we want to identify which policy structure is a better match for subject behavior we need to focus on the 20 Calls treatment, since that is the only treatment where a sample path can lead to different optimal policies. In the 20 Calls treatment, the optimal stochastic and deterministic policies differ in 12% of observations where the subject has free calls, and 49% of cell phone tasks involve at least one such period. When the stochastic and deterministic policies differ, subject's match the SDT threshold in 9.8% of decisions, while they match the DDT threshold in 50.7% of decisions (this difference is significant: signed rank test $p < 0.01$). Furthermore, if we compare a regression specification that predicts the 20 Calls treatment with either just the optimal SDT policy or just the optimal DDT policy, a Vuong test indicates that the optimal deterministic policy provides a significantly better fit($p < 0.01$). This suggests that both the optimal dynamic policies are good predictors of the average behavior of all subjects, however the deterministic heuristic matches average behavior more closely.

Individual Level Comparison of Policies

We next look each subject's profile of 30 choices, and ask which policy structure can best describe that subject. For each subject and each policy structure, we calculate the total absolute difference

[25] While we look at average behavior here, we find consistent results at the individual level. If we compare within a subject the average answer policy used when the optimal policy is 3, 4 or 5 we find that answer policies increase significantly the the optimal policy changes from 3 to 4 and again from 4 to 5 for both the DDT and SDT (signrank test: $p < 0.001$ for all comparison). This suggests that our results for aggregate behavior are not due to selection effects from subjects with different kinds of policies being differentially likely to reach decisions where the optimal policy has increased.

Table 5 Comparison to Optimal Policy

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
# Periods Left	0.0184***	0.0176***	0.00174	0.000965	0.00696***	0.00642***
	(0.00348)	(0.00354)	(0.00240)	(0.00247)	(0.00227)	(0.00223)
Optimal Policy = 4	0.400***	0.520*	0.226**	0.401	0.200**	0.412
	(0.107)	(0.314)	(0.107)	(0.308)	(0.102)	(0.304)
Optimal Policy = 5	1.553***	1.453***	1.263***	1.206***	1.170***	1.120***
	(0.283)	(0.276)	(0.296)	(0.287)	(0.296)	(0.287)
10 Calls Treatment & 0 Calls Left			-0.135	-0.140	-0.101	-0.105
			(0.182)	(0.182)	(0.182)	(0.182)
20 Calls Treatment & 0 Calls Left			-0.316	-0.313	-0.233	-0.229
			(0.193)	(0.191)	(0.186)	(0.185)
10 Calls Treatment & 1+ Calls Left			0.545***	0.551***	0.422*	0.421*
			(0.200)	(0.200)	(0.216)	(0.216)
20 Calls Treatment & 1+ Calls Left			0.499***	0.528***	0.797***	0.829***
			(0.193)	(0.188)	(0.202)	(0.197)
10 Calls Treatment: # Calls Left					0.0154	0.0162
					(0.0132)	(0.0132)
20 Calls Treatment: # Calls Left					-0.0268***	-0.0275***
					(0.00865)	(0.00873)
Task Controls	YES	YES	YES	YES	YES	YES
Constant	2.937***	2.964***	2.998***	3.009***	2.915***	2.923***
	(0.0838)	(0.0841)	(0.138)	(0.138)	(0.139)	(0.139)
Observations	9681	9681	9681	9681	9681	9681
Number of uniqueid	100	100	100	100	100	100

Standard errors clustered at the subject level reported in parentheses. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The dependent variable is the number of calls types answered (e.g. Answer \$0.15 and above is denoted as "5", \$0.30 and above is denoted as "4", etc.) Odd-numbered columns use the optimal SDT policy as the independent variable, while even-numbered columns uses the optimal DDT policy. The specification is OLS with subject random effects, and the observations are restricted to periods where the subject used a threshold policy.

between a subject's policy in each period and the predicted policy for that period. Panel A of Table 6 reports the fraction of subjects who exactly match each policy (i.e. zero total difference), as well as the fraction of subject who have that policy as their closest match (i.e. smallest total difference). Note that these matches are not exclusive, as two (or more) policies can coincide along a sample path. We see that there is a reasonable amount of heterogeneity - particularly in the 20 Calls treatment (where the policies are more likely to differ).

Because many subjects can be explained by more than one policy type, we break this analysis down further for the 20 Calls treatment in Panel B. Here we show the fraction of subjects that have each combination of closest matches that we observe in our data. 55% of our subjects have a unique closest match - with the myopic policy and DDT representing approximately 20% each. Another 10% are equally close to DDT and either static (DST) or SDT, while about 25% are equally close to all three. Finally 10% are equally consistent with all four policy types. Overall, we have 30% of our subjects who can only be described by the static and myopic policies (and are not consistent with a dynamic policy), 30% of our subjects who can only be described by a dynamic policy (and are not consistent with the static and myopic policies), and 40% of subjects whose choices are consistent with both the static and dynamic structures. Hence, while the analysis above indicates that a dynamic policy type is the best single descriptor of the aggregate pattern of choices, there is a substantial fraction of subjects who are definitively using a static policy type.

Panel C reemphasizes the unique description of behavior that our proposed DDT heuristic policy provides. We make pairwise comparisons of the static, DDT and SDT policies, and calculate the fraction of subjects who are consistent with one policy but not the other. When DDT is distinguishable from the static policy almost two and a half times as many subjects are described by DDT. Similarly, when DDT is distinguishable from SDT more than two and a half times as many subjects follow DDT. By contrast, when SDT and static are distinguishable, roughly equal numbers of subjects follow each type.

Table 6 Individual Level Policy Identification

Panel A: Identifying Individual Types

		Myopic	DST	DDT	SDT
10 Calls	**Exact Match**	21.57%	29.41%	29.41%	29.41%
	Closest Match	40.20%	65.69%	65.69%	65.69%
20 Calls	**Exact Match**	10.84%	6.02%	7.23%	4.82%
	Closest Match	30.12%	50.60%	62.65%	46.99%

Panel B: Breakdown of 20-Calls Closest Matches

% Match One Type		% Match 2 or More Types	
Myopic	19.28%	**DST & DDT**	7.23%
DST	8.43%	**DDT & SDT**	2.41%
DDT	18.07%	**DST, DDT & SDT**	24.10%
SDT	9.64%	**All Policies**	10.84%
Total	55.42%	**Total**	44.58%

Panel C: 20-Calls Closest Match Model Comparison

DDT vs DST		SDT vs DST	
DDT but not DST	20.48%	**SDT but not DST**	12.05%
DST but not DDT	8.43%	**DST but not SDT**	15.66%
DDT vs SDT			
DDT but not SDT	25.30%		
SDT but not DDT	9.64%		

"Exact Match" denotes a subject whose profile of choices perfectly coincides with a particular policy. "Closest Match" indicates which policy (or policies) have the smallest total absolute difference from the subject's choices.

5.4. Comparing Decision Rule Calibration to the Optimal Policy

In addition to the decision policy structure, we also want to examine where the average answer threshold is relative to the optimal SDT policy. We have already seen in Figure 2 and Table 2 that subjects are quite liberal in answering low value calls. Figure 4 shows for each treatment the average difference between subjects' actual answer policy and the optimal policy in each period, as well as the percent of subjects who have overused their free calls in each period. Subjects in the 10 and 20 Calls treatment answer too many calls early in the task (when they still have free calls left), while subjects use a policy close to the optimum when they do not have any free calls. Overall, 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.

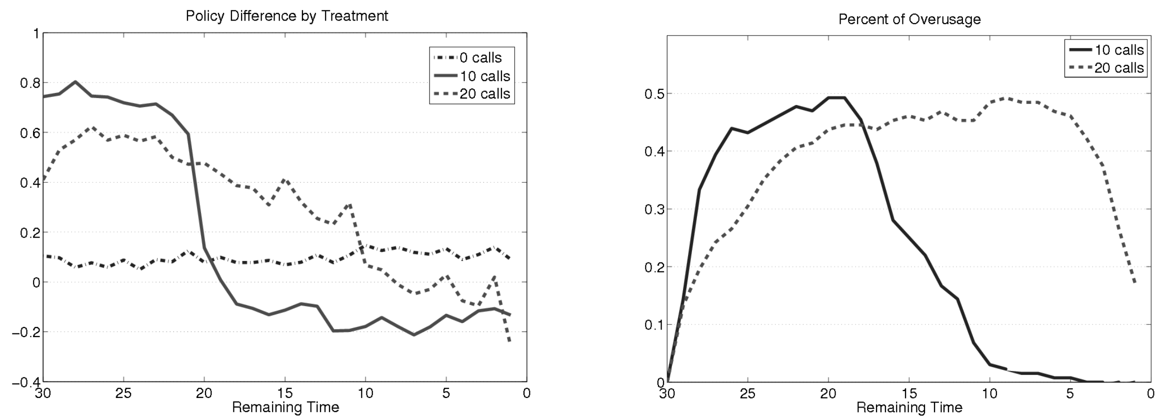


Figure 4 Average Deviation from Optimal Policy and Average Overusage of Free Calls

We confirm these results by regressing the difference between the actual and optimal SDT 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 and third column of Table 7. We also report in the second and fourth column the difference between the actual policy and the optimal DDT policy. For both benchmark optimal policies, the average subject answers significantly more call types than is optimal in both the 10 and 20 Calls treatment, with the size of the deviation decreasing in the 20 calls treatment as the subject has fewer free calls remaining.[26] In both treatments the average deviation from the optimal policy is approximately 0.5 (with no significant difference in the deviation between the treatments - $p > 0.10$ in all specifications). In columns 5 and 6 we conduct a similar analysis using the full data set (i.e. for observations both with and without a threshold policy). We construct an indicator variable that equals 1 if the subject answered the \$0.30 call (or the \$0.15 call) when the optimal policy did not, and then regress that variable on the same set of controls. We find very similar results - subjects with free calls are significantly more likely to incorrectly answer low value calls (for \$0.30 calls this is significant in both treatments, while for \$0.15 calls this is only significant 20 Calls treatment).

[26] We find similar results within an individual subject if we compare average policy differences when the subject is using his first three free calls versus his last three free calls. For both the DDT and SDT the average policy difference is higher when the subject is using his last few calls (signrank: $p < 0.001$ for both).

Table 7 Deviations from Optimal Policy

	Difference From Optimal Policy				Incorrectly Answer	
	Stochastic	Deterministic	Stochastic	Deterministic	\$0.30	\$0.15
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
# Periods Left	0.00732***	0.00489*	0.0120***	0.00961***	0.00614***	0.00258
	(0.00251)	(0.00262)	(0.00333)	(0.00303)	(0.00177)	(0.00161)
10 Calls Treatment & 0 Calls Left	-0.0959	-0.114	-0.0650	-0.0829	-0.0117	-0.0191
	(0.181)	(0.181)	(0.181)	(0.182)	(0.0724)	(0.0715)
20 Calls Treatment & 0 Calls Left	-0.341*	-0.323*	-0.273	-0.255	0.0362	0.0280
	(0.201)	(0.196)	(0.197)	(0.192)	(0.0747)	(0.0982)
10 Calls Treatment & 1+ Calls Left	0.505**	0.522***	0.429**	0.424**	0.145*	0.0973
	(0.198)	(0.199)	(0.213)	(0.215)	(0.0754)	(0.0787)
20 Calls Treatment & 1+ Calls Left	0.324	0.438**	0.546***	0.669***	0.547***	0.308***
	(0.206)	(0.199)	(0.210)	(0.207)	(0.0719)	(0.0889)
10 Calls Treatment: # Calls Left			0.00742	0.0113	-0.00263	-0.00115
			(0.0136)	(0.0135)	(0.00481)	(0.00478)
20 Calls Treatment: # Calls Left			-0.0209**	-0.0218**	-0.0243***	-0.0146***
			(0.00876)	(0.00850)	(0.00403)	(0.00454)
Task Controls	YES	YES	YES	YES	YES	YES
Constant	-0.0841	-0.0513	-0.159	-0.126	0.115**	0.139**
	(0.141)	(0.141)	(0.147)	(0.145)	(0.0547)	(0.0556)
Observations	9681	9681	9681	9681	12120	12120
Number of Subjects	100	100	100	100	101	101

Standard errors clustered at the subject level reported in parentheses, with columns 5 and 6 estimated jointly as seemingly unrelated regressions. Significance is denoted: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$. The dependent variable in columns 1 and 3 is the difference between the subject's answer threshold and the optimal stochastic dynamic threshold. The dependent variable in columns 2 and 4 is the difference between the subject's answer threshold and the optimal deterministic dynamic threshold. The dependent variable in columns 5 and 6 are indicator variables that equal 1 if the subject answered the given call type when the optimal stochastic policy would not. The specification is OLS with subject random effects, and the observations in specification 1 to 4 are restricted to periods where the subject used a threshold policy. The constant term reflects the policy in the 0 Calls treatment.

This over-usage of free calls in turn leads many subjects to answer too many calls in total, and therefore earn less from the cell phone consumption task then the optimal policy would provide. Table 8 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.

Subjects in the 0 Calls treatments earn significantly less than the optimal policy (signrank 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 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 who consistently use a threshold also answer more calls than is optimal ($p < 0.01$), and both threshold using and non-using subjects 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 free calls treatments subject mis-allocate their calls: the average value

Table 8 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	\$4.38	22.24	\$3.95	94%

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.[27]

5.5. Determinants of Overuse

We now examine what behavioral factors can help explain why subjects overuse their free calls. In our data 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.

Table 9 replicates Table 7 while including the difference between subjects' guesses and the expected number of calls as an additional control (we use both the true expectation and the sample-based expectation). Subjects in the 20 Calls treatment who mistakenly overestimate the number of low value calls (which implies undervaluing future consumption opportunities) are significantly more aggressive in using free calls. For the average amount of overestimate, this leads to a predicted increase in the answer policy of 0.11 to 0.13. There is a corresponding decrease in the estimated coefficient for the main treatment effect. This suggests that the mistaken beliefs mechanism explains part (but not all) of the overusage of free calls in the 20 Calls treatment. While the coefficients on beliefs in the 10 Calls treatment are directionally consistent with this mechanism, they are not significant.

[27] We find similar results by comparing actions to the deterministic dynamic threshold - 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)

Table 9 Effect of Mistaken Beliefs

	Difference From Optimal Policy			
	Stochastic		Deterministic	
VARIABLES	(1)	(2)	(3)	(4)
# Periods Left	0.0115***	0.0115***	0.00915***	0.00915***
	(0.00326)	(0.00326)	(0.00297)	(0.00296)
10 Calls Treatment & 0 Calls Left	-0.103	-0.100	-0.119	-0.117
	(0.200)	(0.197)	(0.200)	(0.198)
20 Calls Treatment & 0 Calls Left	-0.432*	-0.436*	-0.401*	-0.402*
	(0.230)	(0.228)	(0.223)	(0.221)
10 Calls Treatment & 1+ Calls Left	0.400*	0.403*	0.397*	0.400*
	(0.233)	(0.230)	(0.235)	(0.231)
20 Calls Treatment & 1+ Calls Left	0.396*	0.391*	0.531**	0.529**
	(0.239)	(0.237)	(0.233)	(0.232)
10 Calls Treatment: # Calls Left	0.00795	0.00793	0.0117	0.0117
	(0.0136)	(0.0136)	(0.0135)	(0.0135)
20 Calls Treatment: # Calls Left	-0.0196**	-0.0196**	-0.0206**	-0.0206**
	(0.00873)	(0.00872)	(0.00844)	(0.00844)
$0.75 Guess - E[# $0.75] & 0 Calls Treatment	0.0156	0.0161	0.0162	0.0168
	(0.0177)	(0.0175)	(0.0177)	(0.0174)
$0.75 Guess - E[# $0.75] & 10 Calls Treatment	-0.0230	-0.0239	-0.0237	-0.0246
	(0.0340)	(0.0339)	(0.0344)	(0.0343)
$0.75 Guess - E[# $0.75] & 20 Calls Treatment	-0.00851	-0.00647	-0.00348	-0.00171
	(0.0326)	(0.0325)	(0.0318)	(0.0316)
$0.15 Guess - E[# $0.15] & 0 Calls Treatment	-0.0170	-0.0179	-0.0171	-0.0180
	(0.0299)	(0.0295)	(0.0302)	(0.0298)
$0.15 Guess - E[# $0.15] & 10 Calls Treatment	0.0109	0.0112	0.0108	0.0111
	(0.0231)	(0.0231)	(0.0232)	(0.0232)
$0.15 Guess - E[# $0.15] & 20 Calls Treatment	0.0498**	0.0498**	0.0435*	0.0437*
	(0.0226)	(0.0226)	(0.0259)	(0.0258)
Task Controls	YES	YES	YES	YES
Constant	-0.154	-0.156	-0.122	-0.125
	(0.166)	(0.163)	(0.164)	(0.161)
Observations	9681	9681	9681	9681
Number of Subjects	100	100	100	100

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

Subjects' mistaken beliefs appear to be 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 experiment. Furthermore, the error in subjects' beliefs was not significantly correlated with the number of sample outcomes they examined.[28]

[28] 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).

We also consider risk aversion, regret aversion, the sunk cost fallacy and cognitive ability as alternative mechanisms.[29] None of these factors can explain our overusage results. Risk aversion, regret aversion and the sunk cost fallacy are not significant predictors of behavior in any treatment, while the only significant effect of cognitive ability is that subjects with lower CRT scores are significantly more conservative (and in fact too conservative) in the 0 Calls treatment.[30] Together this suggests that the overuse bias is partially driven by mistaken beliefs, and otherwise unrelated to the other behavioral factors we measure.

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.

Subjects is this experiment have substantially 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 $p > 0.20$), 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.

[29] Regression results are available upon request from the authors.

[30] 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.

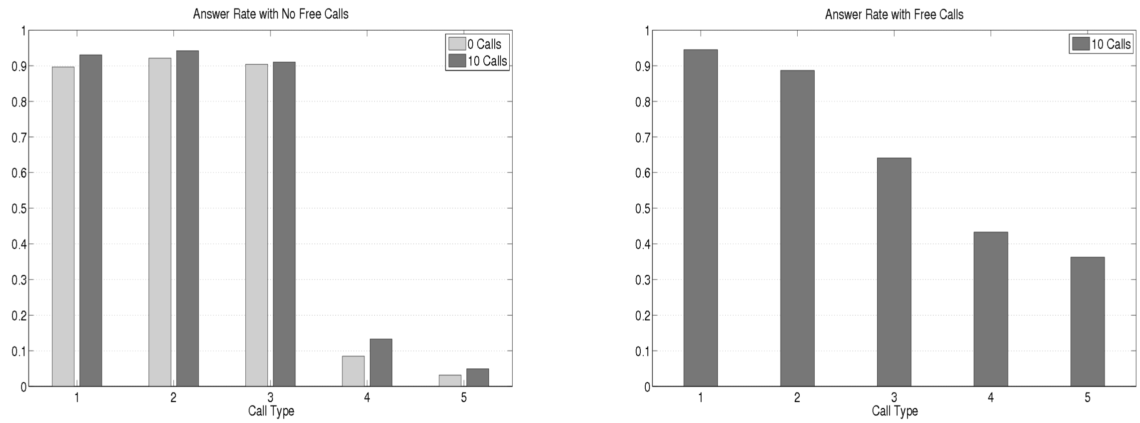


Figure 5 Answer Rates with and without Free Calls

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 stochastic dynamic policy for each call decision. We then replicated the analysis from Table 7 by regressing the deviation from the optimal policy on treatment controls and mistaken beliefs - these results are reported in Table 10.[31] 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 experiment to measure subjects' willingness to pay for a contract with 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 Calls contract and no fee. We again measured risk aversion the sunk cost fallacy, and cognitive ability.[32] 77 subjects participated in this experiment, with 55 providing WTP for ten free calls, and 22 providing WTP for twenty free calls.

[31] We find similar results using the difference between the actual policy and the optimal deterministic dynamic threshold.

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

Table 10 Deviations from Optimal Policy

VARIABLES	(1)	(2)	(3)
# Periods Left	0.00582*	0.00719*	0.00734**
	(0.00308)	(0.00380)	(0.00368)
10 Calls Treatment & 0 Calls Left	-0.0842	-0.0769	-0.0379
	(0.213)	(0.217)	(0.189)
10 Calls Treatment & 1+ Calls Left	0.747**	0.843**	0.857**
	(0.304)	(0.362)	(0.350)
10 Calls Treatment: # Calls Left		-0.0198	-0.0174
		(0.0234)	(0.0227)
\$0.75 Guess - E[# \$0.75] & 0 Calls Treatment			-0.0132
			(0.0343)
\$0.75 Guess - E[# \$0.75] & 10 Calls Treatment			0.000231
			(0.0180)
\$0.15 Guess - E[# \$0.15] & 0 Calls Treatment			-0.00676
			(0.0203)
\$0.15 Guess - E[# \$0.15] & 10 Calls Treatment			-0.0774
			(0.0484)
Task Controls	YES	YES	YES
Constant	-0.283*	-0.301*	-0.266**
	(0.153)	(0.162)	(0.129)
Observations	3957	3957	3957
Number of Subjects	36	36	36

Standard errors clustered at the subject level 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 stochastic dynamic 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 3 uses the true expectation of the value distribution.

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).

Figure 6 shows the demand function that is implied by the distribution of subjects' willingness to pay for each contract (i.e. the fraction of subjects willing to pay at any given price). 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 29% were 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 fewer subjects "overpay", 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

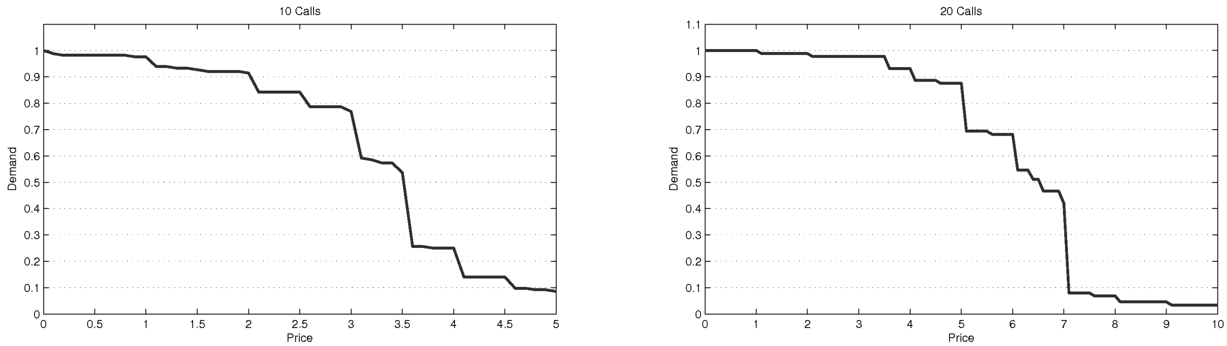


Figure 6 **Willingness to pay distribution for 10 and 20 calls contracts**

worth paying the per-use cost for.[33] 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 11 reports the results of regressing subjects' willingness to pay on various individual characteristics. While we have previously shown that mistaken beliefs significantly influence consumption 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 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 12 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

[33] Note that this means undervaluing the 10 Calls contract also a mistake, since there is negligible option value in this setting. We demonstrate below that WTP in this case is not driven by beliefs, risk attitudes, or cognitive biases. This suggests that undervaluing the contract may reflect either an overestimate of the option value or an aversion to the fixed fee.

Table 11 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			
	(0.0324)				(0.0543)			
\$0.15 Guess - E[# \$0.15]	0.000489				0.0294			
	(0.0298)				(0.0396)			
Risk Aversion		-0.0584				-0.223		
		(0.0435)				(0.175)		
Sunk Cost			0.106				0.756**	
			(0.175)				(0.371)	
CRT Score				-0.00942				0.0572
				(0.0730)				(0.238)
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***
	(0.111)	(0.257)	(0.130)	(0.174)	(0.235)	(1.033)	(0.286)	(0.453)
Observations	220	220	220	220	88	88	88	88
Number of Subjects	55	55	55	55	22	22	22	22

Standard errors clustered at the subject level 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 is OLS with subject random effects.

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 We can identify the revenue maximizing fee for the 10 Calls contract based on three factors: (1) the observed distribution of consumer willingness to pay, (2) the overusage bias for consumers who purchase the 10 Calls contract, and (3) and the estimated effects of price on behavior estimated above in Table for subjects who end up with the pay-per-use 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 54% of consumers purchasing

Table 12 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	
	(0.662)		(0.384)		(0.258)		(0.225)	
WTP		-0.882*		0.183		0.0447		0.152
		(0.526)		(0.621)		(0.280)		(0.278)
Constant	23.93***	21.33***	19.57***	19.26***	20.94***	19.52***	24.46***	22.75***
	(2.481)	(1.515)	(0.781)	(2.097)	(1.706)	(1.535)	(0.844)	(1.872)
Observations	81	81	139	139	34	34	54	54
Number of Subjects	47	47	55	55	19	19	21	21

Standard errors clustered at the subject level 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.

the contract, generating an average revenue of $6.88 per customer[34] - a 14.0% increase over the estimated average revenue of $6.04 if the firm does not offer a presale contract. Any price between $3.01 and $4.00 would lead to a revenue increase of up to 10%, and any price above $2.35 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 14.2%. 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 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 3.0%. 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.[35] This fee leads to 47% of consumers purchasing the contract, generating 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 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%.

[34] The overusage bias would lead customers with the 10 Calls contract to answer on average 10.03 calls beyond their initial endowment of ten free calls, yielding the firm a total revenue of $7.00 from this segment. For consumers with the 0 Calls contract the price effect would lead them to answer on average 19.28 calls, generating a total revenue of $6.75.

[35] 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.

It is interesting to note that if a firm were to only offer one contract with free calls, it would prefer to offer the 10 Calls contract. The 10 Calls contract leads to almost twice the increase in revenue as the 20 Calls contract. The 10 Calls contract provides two advantages to the firm. First, more consumers overvalue the 10 Calls contract than the 20 Calls contract, leading to greater uptake of the contract at the optimal price. Second, the firm benefits from consumer overusage by not providing too many free calls, so that there is a greater number of periods that consumers pay the per-use fee.

8. Discussion and Concluding Remarks

In this paper we consider several plausible decision heuristics that consumers may use in consuming access services. A deterministic dynamic 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 stochastic dynamic policy, but is much easier to calculate. 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 both the stochastic and deterministic policies in many cases. Additionally, the deterministic dynamic policy provides the best single description of average consumer behavior. 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 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 14%.

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) estimate 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 used in Grubb and Osborne. On the positive side, we find supportive evidence that consumers use heuristics to simplify the consumption problem, and that many consumers may have mis-calibrated decision rules. On the other hand, we find that a substantial fraction of subjects adjust their threshold[36], 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 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.

[36] In Grubb and Osborne's data consumers were not able to find out how many minutes they had left, while in our experiment subjects remaining calls were always displayed. Hence, we believe that Grubb and Osborne's assumption of complete inattentiveness is likely a good assumption for their data, but may not generalize to settings where consumers can more easily track their usage.

References

Arkes, H. R., and C. Blumer, “The psychology of sunk costs”, *Organizational Behavior and Human Decision Processes* 35, 124-140(1985).

Ascarza, E., A. Lambrecht, and N. Vilcassim, (2009) “When Talk is “Free”: An Analysis of Subscriber Behavior under Two- and Three-Part Tariffs”, working paper. London Business School.

Barz, C., and K. H. Waldmann, “Risk sensitive capacity control in revenue management”, *Math. Meth. Oper. Res.* (2007) 65: 565-579.

Bearden, J. N., R. O. Murphy, and A. Rapoport, “Decision Biases in Revenue Management: Some Behavioral Evidence”, *Manufacturing and Service Operations Management* 10-4, 625-636, 2007.

Bertini, M., and L. Wathieu, “Attention Arousal through Price Partitioning”, *Marketing Science*, Vol. 27, No. 2, 2008.

Bitran, G., P. Rocha e Oliveira, and A. Schilkrut, “Managing customer relationships through pricing and service quality”, working paper, 2008.

Borenstein, S., “To What Electricity Price Do Consumers Respond? Residential Demand Elasticity Under Increasing Block Pricing”, 2009.

Cachon, G. and P. Feldman, “Pricing services subject to congestion: Charge per-use fees or sell subscriptions?”, *Manufacturing and Service Operations Management*, vol. 13, No.2 pp. 244-260 2011.

Cox, J. C., and R. L. Oaxaca. “Laboratory experiments with a finitehorizon job-search model”, *J. Risk Uncertainty*, 2 301330 (1989).

DellaVigna, S., and U. Malmendier, “Paying Not to Go to the Gym”, *The American Economic Review* June 2006, Vol. 96, pp. 694-719.

DellaVigna, S., and U. Malmendier, “Contract Design and Self Control: Theory and Evidence”, *The Quarterly Journal of Economics* May 2004, Vol. 119, pp. 353-401.

Eliaz, K. and R. Spiegler, “Contracting with Diversely Naive Agents”, *The Review of Economic Studies*, 2006, 73 (3), 689-714.

Eliaz, K. and R. Spiegler, “Consumer Optimism and Price Discrimination”, *Theoretical Economics,* 3(4), 459-497 (2008).

Esteban, S., E. Miyagawa and M. Shum, “Nonlinear Pricing with Self-Control Preferences”, *Journal of Economic Theory*, 135, 306-338 (2007).

Iyengar, R., K. Jedidi, S. Essegaier, and P.J. Danaher “Shaping Value of Access Services through Pricing Structure”, (2010) working paper.

Frederick, S. “Cognitive Reflection and Decision Making” *Journal of Economic Perspectives*, 19(4), pp. 25-42 (2005).

Gallego, G., and Şahin, Ö., "Revenue Management with Partially Refundable Fares", forthcoming in *Operations Research* (2010).

Grubb, M., "Selling to Overconfident Consumers", *American Economic Review*, 99(5), pp. 1770-1807 (2009).

Grubb, M., and M., Osborne, "Cellular service demand: Tariff choice, usage uncertainty, biased beliefs, and learning", (2011) working paper.

Holt, C. A. and S. K. Laury, "Risk Aversion and Incentive Effects", *American Economic Review* 92(5), pp. 1644-55 (2002).

Kridel, D. J., D. E. Lehman, and D. L. Weisman, "Option Value, Telecommunication Demand, and Policy", *Information Economics and Policy*, 5 (2), 125-44 (1993).

Lambrecht, A. and B. Skiera (2006), "Paying Too Much and Being Happy About It: Existence, Causes and Consequences of Tariff-Choice Biases", *Journal of Marketing Research*, 43 (May), 212-23.

Lambrecht, A., Seim, K., and B. Skiera, "Does Uncertainty Matter? Consumer Behavior Under Three-Part Tariffs", *Marketing Science*, Vol. 26, No. 5, 698-710, 2007.

Liebman, J., and R. Zeckhauser, "Schmeduling, Manuscript, Harvard University, 2004.

Loewenstein, G., T. O'Donoghue, and M. Rabin, "Projection bias in predicting future utility", *The Quarterly Journal of Economics*, 2003, 118 (4), 1209-1248.

Miravete E.J. "Estimating Demand for Local Telephone Service with Asymmetric Information and Optional Calling Plans", *Review of Economic Studies*, 69, 943-971 (2002).

Miravete E.J., "Choosing the Wrong Calling Plan? Ignorance and Learning", *American Economic Review*, Vol. 93 (1), 297-310 (2003).

Narayanan, S., Chintagunta, P., and Miravete E.J."The Role of Self-Selection, Usage Uncertainty and Learning in the Demand for Local Telephone Service", *Quantitative Marketing and Economics*, 5, 1-34 March 2007.

Nunes, J., "A Cognitive Model of People's Usage Estimations", *Journal of Marketing Research*, 37 (November), 397-409 (2000).

Oster, S M. and F. M. Scott Morton, "Behavioral Biases Meet the Market: The Case of Magazine Subscription Prices", *Advances in Economic Analysis & Policy*, 2005, 5 (1).

Papastavrou, J., Rajagopalan, S., and Kleywegt, A. J., "The Dynamic and Stochastic Knapsack Problem with Deadlines", *Management Science*, Vol. 42, No.12, 1706-1717 1996.

Plambeck, E., and Q. Wang, "Implications of Hyperbolic Discounting for Optimal Pricing and Scheduling of Unpleasant Services that Generate Future Benefits", 2011, working paper.

Prelec, D. and G. Loewenstein (1998), "The Red and the Black: Mental Accounting of Savings and Debt", *Marketing Science*, 17 (1), 4-28.

Randhawa, R. and S. Kumar. "Usage restriction and subscription services: Operationa; benefits with rational users", *Manufacturing and Service Operations Management*, vol.10 3 429-447 2008.

Savage, S. L., "The Flaw of Averages: Why We Underestimate the Risk in the Face of Uncertainty," John Wiley & Sons Inc. Hoboken New Jersey 2012.

Schotter, A., Y. M. Braunstein, "Economic search: An experimental study", *Econom. Inquiry* 19 125 (1981).

Soman, D. "Effects of Payment Mechanisms on Spending Behavior: The Role of Rehearsal and Immediacy of Payments", *Journal of Consumer Research,* 27 (March), 460-74 (2001).

Wilson, R. (1993), "Nonlinear Pricing". New York: Oxford University Press.

Train, K., D. L. McFadden, and M. Ben-Akiva , "The Demand for Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices", *Rand Journal of Economics*, 18 (1), 109-123 (1987).

Train, K.E., M. B. and T. Atherton, "Consumption Patterns and Self-Selecting Tariffs", *Review of Economics and Statistics*, 1, 62-73 (1989).

Thomas, M. and V.G. Morwitz , "Penny Wise and Pound Foolish: The Left Digit Effect on Price Cognition", *Journal of Consumer Research*, 32, 54-64 (2005).

Xie, J., and S. Shugan, "Electronic Tickets, Smart Cards and Online PrePayments: When and How to Advance Sell", *Marketing Sci.*, 21 (2001) 219-243.

Yao, S., C. F. Mela, J. Chiang, Y. Chen, "Determining Consumer's Discount Rates with Field Studies," 2011.

Zeelenberg, M., J. Beattie, J. van der Pligt and N.K. de Vries, "Consequences of Regret Aversion: Effects of Expected Feedback on Risky Decision Making", *Organizational Behavior and Human Decision Processes*, 65, 148-158 (1996).

Zeelenberg, M. and J. Beattie, "Consequences of Regret Aversion 2: Additional Evidence for Effects of Feedback on Decision Making", *Organizational Behavior and Human Decision Processes*, 72, 63-78 (1997).