The Role of Self Selection, Usage Uncertainty and Learning in the Demand for Local Telephone Service

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Abstract

Telephone services are often characterized by the presence of 'fixed' plans, involving only a fixed monthly fee, as well as 'measured' plans, with both fixed fees and per-unit charges for usage. Consumers are faced with the decisions of which plan to choose and how much to use the phone and these decisions are not, in general, independent. Due to the presence of a time lag between plan choice and usage decisions, consumers are uncertain about usage at the plan-choice stage. We develop a structural discrete/continuous model of plan choice and usage decisions of consumers that accounts for such uncertainty. Prior research has also found that consumers switch less often from fixed plans to measured plans to gain from potential savings than vice versa. Consumer uncertainty regarding their mean usage levels and different rates of learning by consumers in the two plans is a potential explanation for this phenomenon. We extend our discrete/continuous model to account for consumer learning about their mean usage and estimate different rates of learning for the two types of plans.

We estimate our model using data from the 1986 Kentucky local telephone tariff experiment. Even in the absence of any price variation over time, we are able to measure the price elasticities both of usage and of choice of plan. Using our parameter estimates, we simulate the effects of the introduction of a metered plan in a market with only a fixed plan and vice versa, on both firm revenues and consumer surplus. We also find that consumers learn very rapidly if they are on the measured plan but learn very slowly when they are on the fixed plan. We investigate an alternative assumption on the nature of the learning process in which only consumers in the measured plan have an opportunity to learn. We find that our empirical results are robust to this change of specification. We conduct counterfactual simulations to simulate enhanced calling plans from the firm and consumer points of view. Additional simulations to measure the value of information in this category are also carried out. We compute the value of both complete information, where the entire uncertainty about future usage is resolved, as well as that of limited information, where the consumer's uncertainty about mean usage is resolved, but the uncertainty about specific month-to-month usage remains. We find that the value of information is modest. We also find that a large proportion of the value of information is that about the mean usage, with the value of the information about a specific month's usage being relatively small.

Keywords: *Self-selection, Uncertainty, Value of Information, Discrete/Continuous Models, Learning Models, Telecommunications, Optional Calling Plans.*

JEL Classification: D12, D83, K23, L11, L96, M31

Several subscription-based services (e.g. local telephone service, cellular telephone service, internet access) use non-linear pricing schemes that involve a fixed access fee and a marginal price for usage of the service. Consumers are often offered a menu of tariff plans, in which the access-fee and the marginal price differ, but the service offered is the same across these plans. Different tariff plans are cost minimizing to the consumer at different levels of usage. However, it has been documented in the literature (e.g. Train, McFadden and Ben-Akiva 1987) that consumers seemingly make mistakes when they choose these plans – i.e. they seem to often choose plans that are not cost minimizing. This behavior has been rationalized in the literature by the presence of uncertainty about future usage at the time of plan choice (Miravete 2002). This literature also finds evidence that consumers switch plans to correct these “mistakes”, providing evidence for learning. Another characteristic feature of such markets is that consumers are sticky to fixed-rate plans, but not to measured-rate plans i.e. they switch out of sub-optimal plans more often when they are measured-rate plans than when they are fixed-rate plans (Hobson and Spady 1988; MacKie-Mason and Lawson 1993).

In this paper, we develop a structural model of plan choice and usage decisions that specifically accounts for this uncertainty about future usage at the time of plan choice. The model also accounts for learning by consumers to resolve uncertainty about their usage levels. We propose that asymmetries in information content in the two kinds of plans and consequent asymmetries in learning by consumers of the two plans explain the stickiness to fixed rate plans. Hence, we allow for differential learning by consumers of fixed and measured plans to account for asymmetric switching behavior for the two plans. A structural model is important because our objective is to use these estimates to conduct counterfactual simulations to measure the impact of pricing policies on consumer surplus and firm revenues and also to measure the economic significance of uncertainty. For our empirical analysis, we use a dataset from a tariff pricing field experiment run by South-Central Bell in the local telephone service market in 1986. In this experiment, consumers who previously did not have optional plans to choose from and were all on a fixed-rate plan were offered the choice of an additional measured-rate plan and their choices and usage were monitored for a period of three months. As we shall discuss later, these data are uniquely suited to study the research questions we are interested in answering.

In the case of subscription-based services such as those we are interested in, consumers typically make two kinds of decisions. They make a discrete choice of a tariff plan from amongst the available menu options. And they subsequently make usage decisions at later points of time. Thus, discrete/continuous models (Hanneman 1984) are particularly well suited to model such behaviors. However, these models cannot be directly applied to these data since they assume that both the discrete and continuous decisions are made simultaneously. Hence, there is no uncertainty about the continuous decision at the time of discrete choice. By contrast, the temporal separation between the discrete choice and continuous decisions and the consequent uncertainty about the continuous decision at the time of discrete choice is an important characteristic of subscription-based services. As we have pointed out earlier, seemingly irrational "mistakes" are rationalized by taking this uncertainty into account. Hence, we need to modify the standard class of discrete/continuous models to specifically incorporate uncertainty.

We first specify a structural model of plan choice and usage that takes into account the two-stage decision making process. Consumers are assumed to have a conditional indirect utility that is a function of a consumer specific "type." A consumer's type depends upon a consumer-specific mean usage, the effects of consumer characteristics and two types of unobservables (from the perspective of the researcher). One of these is observed by the consumer at the time of plan choice each month (the "plan shock") whereas the other is not. The latter is revealed to the consumer at the time of usage (the "usage shock") and it is the presence of this shock that explains consumer plan choices that do not appear to be "optimal" ex-post. The consumer-specific mean usage accounts for heterogeneity in usage levels. From the indirect utility function we derive the condition that determines a consumer's plan choice. Using Roy's identity we also obtain the usage level. We then write out the joint likelihood of plan choice and usage level that we can take to the data. Unlike previous discrete / continuous models that have used a two-step estimation method for obtaining the model parameters, we obtain efficient maximum-likelihood estimates by maximizing the joint likelihood directly.

We then extend the basic model to reflect another important feature of the data – the nature of switching behavior between plans. While the total amount of switching is small, we observe that a majority of those who switch from the measured plan (into the fixed plan) do so because they would be better off under the fixed plan. On the other had, a much smaller fraction of those who switch from the fixed plan (into the measured plan) do so because the fixed plan is sub-optimal for them. A characteristic of the two plans is that the telephone company provides a detailed report of calling activity for those under the measured plan but does not do so for those under the fixed plan. Hence it is possible that the consumers may not be fully informed not just about their usage shock in each month but also their true mean usage level. And access to a detailed report of calling may enable consumers under the measured plan to learn about their true mean usage level. Such learning may be much slower or not at all for consumers when they are on the fixed plan. We incorporate such learning behavior in two alternative ways into our proposed discrete/continuous demand model described previously.

Using our parameter estimates, we compute the elasticities of plan choice and usage to prices. This computation is of value since the markets for several subscription-based services see very little price variation over time, unlike in the case of grocery products or many other categories. Hence, it is hard, if not impossible, to estimate price elasticities, especially usage elasticities by merely studying usage behavior over time. Due to our unique modeling approach, where we model both plan choice and usage decisions simultaneously, we are able to compute both choice and usage elasticities.

We also conduct a series of counterfactual simulations to answer interesting research questions. In one set of simulations, we find impact on firm revenues and consumer surplus of adding an additional measured-rate plan to an existing fixed-rate plan or vice versa. As a result, we measure the impact of the availability of choice of tariff plans on overall welfare.

In a second set of simulations, we find alternative plans that increase overall welfare. Instead of finding the pricing policy that maximizes welfare, which is a challenging problem to solve, we take the simpler approach of finding alternative plans that strictly increase consumer surplus while keeping firm revenues unchanged or alternatively raise firm revenues while keeping consumer surplus unchanged.

Finally, we conduct a set of counterfactual simulations to measure the economic significance of uncertainty. We do this by finding the amount of money consumers would be willing to pay to resolve their uncertainty about future usage, i.e. the value of information. We compute this value of information for two levels of uncertainty – uncertainty about one's mean level of usage and uncertainty about variations in usage from month to month.

The primary substantive contribution of this paper is our finding that subscription to different tariff plans provides differential information to consumers. Specifically, we find that consumers who are on measured plans learn faster about their own usage levels and this could help them make better choices in the future, while consumers on fixed plans learn very slowly about their usage. The informational difference between fixed and measured plans provides a rationalization for why consumers are observed to be stickier to fixed plans than to measured plans. This is also, to our knowledge, the first study that measures the value of information in this context of choice amongst two-part tariffs with uncertain future usage. Another contribution of this study is that we provide a rational framework in which consumers of two-part tariff plans may choose plans that are suboptimal *ex-post*, but learn from their mistakes and make better choice decisions in the future. Furthermore, we conduct several interesting counterfactual simulations to understand the impact of tariff plan pricing on consumer surplus and firm revenues. The primary methodological contribution of this study is in developing a discrete/continuous model of demand under a situation of uncertainty. Past research using discrete/continuous models has assumed that there is no uncertainty at the time of discrete choice. In this study, we demonstrate how to incorporate uncertainty in the model and show how such a model can be estimated. We model learning by consumers in this context and develop two alternative specifications for such learning.

The remainder of this paper is organized as follows. We first discuss the related literature briefly and detail the primary contributions of our paper, relating it to the extant literature. Then we discuss the model in depth and derive a discrete/continuous model of plan choice and usage in which consumers are uncertain about their actual usage in each month when making their plan choice but know their mean usage levels. Subsequently, we extend the model to allow for uncertainty in mean usage levels and incorporate learning about these usage levels. We propose two alternative specifications to incorporate learning. Next, we discuss the estimation of the models, lay out the empirical details and discuss the identification of model parameters. We then provide our empirical results, giving interpretations to the parameter estimates. Subsequently, we discuss a set of counterfactual simulations to measure the value of information to consumers and other counterfactual simulations to understand the implications of plan availability and pricing for firm revenues and consumer surplus as these are metrics of interest to the firm as well as to the regulator. We conclude, discussing future directions of this research and describing the limitations of our study.

1. Literature Review

The related literature for this paper can broadly be classified into three groups. The first group consists of papers related to non-linear pricing. There is a lot of recent interest in the literature on two-part and three-part tariffs and we shall relate our study to these papers in the literature. The second group consists of papers that we draw from in terms of methodology. This includes the studies on discrete/continuous models of demand. The third stream of literature that is of relevance is the one on measuring the value of information.

A number of studies in the literature have documented the apparent "mistakes" that consumers make when they choose a tariff plan. It turns out that for a significant set of consumers, the plan they chose is not the cost-minimizing plan. An early paper that documented such behavior was Train, McFadden and Ben-Akiva (1987). Other studies that have documented this phenomenon are Hobson and Spady (1988), MacKie-Mason and Lawson (1993) and Miravete (2002). Miravete (2002) rationalizes such behavior by suggesting that uncertainty about future usage might imply that consumers make ex-post suboptimal decisions even while making optimal decisions ex-ante. He demonstrates that on average, consumers choose cost-minimizing plans and thus self-select into plans that are optimal given their average levels of usage. Some recent empirical studies (Lambrecht, Seim and Skiera, 2005; Huang 2006; Goettler and Clay 2006) have also looked at the issue of demand uncertainty in the context of subscription-based services. This literature suggests that it is important to explicitly account for uncertainty in future usage at the time of plan choice in any structural model, in order to account for these "mistakes".

Miravete (2002) documents that while consumers might make ex-post mistakes, they also switch plans in order to save costs. He also documents an interesting asymmetry in switching behavior between fixed and measured tariff plans. Consumers in measured plans make more mistakes but also rapidly switch to the fixed plan if that is cost minimizing for them. Thus, he finds evidence for learning by consumers about their usage levels. In our model, we incorporate learning by consumers about their own usage levels and also allow for asymmetries in learning behavior between the two kinds of plans. This provides a new explanation for the greater stickiness to fixed than measured plans that has been documented in the literature (e.g. Hobson and Spady 1988; MacKie-Mason and Lawson 1993).

Two other recent studies have also looked at learning in the context of two-part or three-part tariffs. Goettler and Clay (2006) specify a dynamic structural model of learning in the context of two-part tariffs for an online grocery service. In their case, consumers are uncertain about the quality of the service and learn about it through their usage experience. By contrast, in our case, consumers learn about their usage levels, rather than the quality of service. In our case, the quality of service is the same across different options and hence does not affect the consumer's plan choice decision. Another recent study that looks at consumer learning in the context of three-part tariffs for cellular telephone services is Iyengar, Ansari and Gupta (2006).

One important difference of our study from theirs is that while we build a structural model where both plan choice and usage decisions flow from a single utility function and consumers account for uncertainty in usage at the time of plan choice, in their case usage is a reduced-form deviation from optimal usage levels. Indirect evidence for learning in the case of cellular telephone service is also presented by Iyengar (2004).

Another stream of literature that informs our modeling approach is that on discrete/continuous models of choice. The seminal papers in this literature include Dubin and McFadden (1983) and Hanneman (1984). Such models have been applied to a variety of contexts in the empirical literature in marketing (c.f. Chiang 1991; Chintagunta 1993; Nair, Dube and Chintagunta 2005; Song and Chintagunta 2006). A key assumption of these papers is that the discrete choice and continuous choice are made simultaneously. Hence, there is no uncertainty about the continuous decision at the time of the discrete choice. By contrast, as we have pointed to earlier, uncertainty in the continuous decision at the time of discrete choice is critical to rationalizing the ex-post mistakes that consumers are seen to make in the markets for various subscription-based services. Hence, we need to modify the standard discrete/continuous models to build in this uncertainty in the continuous decision at the time of discrete choice. We need to allow consumers to be aware of this uncertainty and take it into account when they make the discrete choice.

There is one other study in the literature that attempts to do this. Economides, Seim and Viard (2004) estimate a model for choice and usage of local telephone service. While there are some similarities in the modeling approaches in their study and ours, the focus of the studies are very different. Their research question of interest is to measure the welfare effects of entry of competitors in a monopoly market. By contrast, our focus is on understanding the role that uncertainty plays in consumer behavior and to measure its economic significance. Additionally, we study learning and asymmetries in learning across fixed and measured plans.

A final stream of literature that is of relevance to this study is that on the value of information. Our context is one where consumers make decisions under uncertainty and thus end up making choices that are potentially sub-optimal *ex post*. Hence, it would be interesting to measure the value of information that would resolve this uncertainty and allow them to make choices that are optimal *ex post*. Recent research (Chernew, Gowrisankaran and Scanlon 2006; Jin and Sorensen 2005) on health-plan choices in the context of uncertainty about the quality of these health plans attempts to measure the value of information provided by health plan ratings. We use an approach similar to that used in these studies to measure the value of information that would resolve the consumer's uncertainty at the time of plan choice.

To summarize this discussion, some of the key findings of prior research are that (a) it is important to account for the fact that consumers self select the choice of calling plan and decide on usage (b) information uncertainty about actual usage at the time of plan choice could explain the apparent mistakes that consumers make in the choice of plan. (c) consumers seem to learn about their own usage patterns through the usage of the local telephone service and switch plans to save costs (d) there could be some asymmetry in this learning between fixed and measured plans: consumers may learn at different rates from their usage of different plans.

We propose to integrate the above findings that have been obtained from a diverse set of models and data and develop a single structural model of local telephone calling plan choice and its usage. The goals of this research are therefore to: (i) develop a model of demand, consisting of plan choice and usage, in this situation of uncertainty about usage at the time of plan choice; (ii) evaluate formally if consumers learn about their own usage patterns through observing their own calling patterns and find if there are asymmetries in learning between fixed and measured plans; (iii) measure the value of information that would resolve consumers' uncertainty about their mean usage as well as that about their month to month usage; and (iv) understand the effects on consumer surplus and firm revenues of changes to the optional calling plans. While the modeling approach and framework are of potential interest to marketing researchers, the substantive results would have implications for managers and regulators.

2. Model

2.1 Base Model

Consumers make two decisions in each time period regarding their local phone service. The two decisions are the choice of the tariff plan to subscribe to and the usage of the local phone service. The choice of plan is a discrete choice amongst available options while usage is a continuous choice. Thus, the model needs to incorporate this discrete/continuous nature of the consumer decision process. There is no decision made by consumers about which provider to use for the local phone service as this is a regulated monopoly. Consumers may potentially make the decision whether to use local phone service or not have a telephone at all. However, we do not model this decision as all consumers in our data chose to maintain local telephone calling service. We also note that at the time of our data cellular telephones had not seen widespread adoption. In Louisville, 92% of households were subscribed to local telephone service at the time the SCB tariff experiment was conducted. Thus, we believe that our assumption that there are only two decisions made by consumers – the choice of plan and usage – is reasonable.

We adopt the assumption in Miravete (2002) that consumers have a two-stage decision process. In the first stage, they choose which plan to subscribe, without knowing exactly what their usage would be, though they have some beliefs about their usage. Subsequently, consumers make a decision on how much to use the phone service. This separation of the plan choice from the usage decision is an important assumption since it helps explain the apparent 'mistakes' that consumers make. The apparent mistakes of consumers, i.e. situations where they could have saved money by choosing a different plan, can be explained in a rational framework by the fact that when consumers make their plan choice decisions, they are uncertain about the realization of usage. Thus, they can be *ex-ante* optimal decisions even if they appear to be mistakes *ex-post*. This was one of the main results demonstrated by Miravete (2002).

Another assumption we make is that there are no switching costs between plans. Thus, consumers are assumed to make plan choice decisions in every period, without having to worry about costs of switching to a different plan than their current one. This is a reasonable assumption since there were no explicit switching costs in the tariff experiment that constitutes our dataset for analysis. We assume away any intangible switching costs (e.g. the mental and time costs involved in processing information about different plans before making a decision to switch to a different plan). We recognize however, that such switching costs can potentially account for stickiness in plan choice as has recently been demonstrated by Moshkin and Shachar (2002) in the context of television viewing.

When making plan choice and usage decisions at time t, consumer i is assumed to maximize the following conditional indirect utility function, where j indicates the calling plan

(1) $$V_{it}^{j} = \left(y_i - f^{j}\right) + \frac{\theta_{it}}{\beta}\exp\left(-\beta p_t^{j}\right)$$

$$\beta, \theta_{it} > 0$$
$$p_t^{j}, f^{j} \geq 0$$

y_i is the income

θ_{it} is an individual and time specific *type*

f^{j} is the fixed fee for plan j

p_t^j is the per-unit price for usage (which is 0 in the case of the fixed-rate plan)

β (> 0) is a parameter, common to all consumers and $-\beta$ plays the role of the price coefficient in the model

Let

(2) $$\ln(\theta_{it}) = \alpha_i + \gamma Z_{it} + \eta_{it} + \nu_{it}$$

and $$\begin{pmatrix} \eta_{it} \\ \nu_{it} \end{pmatrix} \sim N(0, \Sigma)$$

where $$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix}$$

The consumer and time specific *type* thus has three components. The first is a consumer-specific but time-invariant component α_i. The second component, $\gamma Z_{it} + \eta_{it}$, is observed by the consumer at the time of plan choice and consists of a systematic component γZ_{it} and a consumer and time period specific random shock η_{it}. The third component, ν_{it}, is a random shock that is not observed at the time of the plan choice decision but is revealed at the time of the usage decision. We shall refer to α_i as the consumer's type, η_{it} as the choice shock and ν_{it} as the usage shock. By allowing Σ to be a non-diagonal matrix, we allow the plan choice shock η_{it} and the usage shock ν_{it} to be correlated. This explicitly corrects for any selection problem that may be present.

Z_{it} is a set of time and consumer specific variables, including demographic variables, month dummies and any other variables that vary both with consumer and time. In our empirical application, we only have demographic variables (that vary with consumers but not with time) and month dummies (that vary with time but not with consumers).

At the time the consumer makes the plan choice decision, she is assumed to know all parameters of her utility function except ν_{it}. This is assumed to be revealed after the plan choice is made but before the usage decision is made. However at the time of the plan choice, the parameters σ_{11}, σ_{22} and σ_{12} are assumed to be known by the consumer. This uncertainty about the realized value of ν_{it} at the time of plan choice accounts for the assumption that there is a temporal separation between the plan choice and usage decisions.

The utility function described above is closely related to the one in Hobson and Spady (1988). We discuss here certain features of the utility that are pertinent to us and are not discussed in that paper.

Note in equation (1), that the marginal utility of income is the coefficient of $\left(y_i - f^j\right)$ in this model and is hence equal to one. We have fixed the marginal utility to one since it is not identified. If we were to add a marginal utility term as a multiplicative coefficient to $\left(y_i - f^j\right)$ in equation (1), it turns out that in the estimation equations for plan choice and usage (derived in subsequent sections), it enters additively with the parameter α_i. Hence, the estimated parameter α_i could be interpreted as the combined effect of α_i and the marginal utility of income.

As would be seen when we derive consumption (usage), our utility function gives downward sloping demand. We will also see that a feature of this utility function is that users with high usage are more likely to choose fixed plans, whereas those with usage below a certain threshold are more likely to choose the measured plan. Another feature of this utility function is that consumers are assumed to be risk-averse agents[1].

2.1.1 Plan Choice

The two plans that the consumer chooses between are

1. Fixed plan – this plan has a fixed fee of f^F and no per-minute usage charges
2. Metered plan – this plan has a fixed fee of f^M and per-minutes usage charges p_t^M

The conditional indirect utilities of using these plans are given by

$$V_{it}^F = \left(y_i - f^F\right) + \frac{\theta_{it}}{\beta} \tag{3}$$

$$V_{it}^M = (y_i - f^M) + \frac{\theta_{it}}{\beta}\exp\left(-\beta p_t^M\right) \tag{4}$$

Since ν_{it} is stochastic to the consumer at the time of plan choice, θ_{it} is also stochastic. Hence, she chooses the plan that gives the higher expected utility, with the expectation taken over the distribution of ν_{it}, conditional on η_{it}.

The consumer chooses the metered plan if the expected utility of using that plan is higher

$$E_{\nu_{it}|\eta_{it}}\left[V_{it}^M\right] > E_{\nu_{it}|\eta_{it}}\left[V_{it}^F\right] \tag{5}$$

$$\Rightarrow E_{\nu_{it}|\eta_{it}}\left[(y_i - f^M) + \frac{\theta_{it}}{\beta}\exp\left(-\beta p_t^M\right)\right] > E_{\nu_{it}|\eta_{it}}\left[\left(y_i - f^F\right) + \frac{\theta_{it}}{\beta}\right] \tag{6}$$

$$\Rightarrow E\left[\theta_{it}\right] < \frac{\left(f^F - f^M\right)\beta}{1 - \exp\left(-\beta p_t^M\right)} \tag{7}$$

Substituting the value of θ_{it} from (2), the condition of choice of metered plan is given by

[1] This can be verified by writing the direct utility function corresponding to the indirect utility function in equation (1). More details on the direct utility function and the derivation of the coefficient of risk aversion are available from the authors on request.

(8) $$E_{\nu_{it}|\eta_{it}}\left[\exp\left(\alpha_i+\gamma Z_{it}+\eta_{it}+\nu_{it}\right)\right]<\frac{\left(f^F-f^M\right)\beta}{1-\exp\left(-\beta p_t^M\right)}$$

(9) $$\Rightarrow E_{\nu_{it}|\eta_{it}}\left[\exp\left(\alpha_i+\gamma Z_{it}\right)\exp\left(\eta_{it}\right)\exp\left(\nu_{it}\right)\right]<\frac{\left(f^F-f^M\right)\beta}{1-\exp\left(-\beta p_t^M\right)}$$

Noting that

(10) $$\nu_{it}\mid\eta_{it}\sim N\left(\frac{\sigma_{12}}{\sigma_{11}}\eta_{it},\frac{\sigma_{11}\sigma_{22}-\sigma_{12}^2}{\sigma_{11}}\right)$$

(11) $$\begin{aligned}&E_{\nu_{it}|\eta_{it}}\left[\exp\left(\alpha_i+\gamma Z_{it}\right)\exp\left(\eta_{it}\right)\exp\left(\nu_{it}\right)\right]\\&=\exp\left(\alpha_i+\gamma Z_{it}\right)\exp\left(\eta_{it}\right)E\left[\exp\left(\nu_{it}\mid\eta_{it}\right)\right]\\&=\exp\left(\alpha_i+\gamma Z_{it}+\left(1+\frac{\sigma_{12}}{\sigma_{11}}\right)\eta_{it}+\frac{\sigma_{11}\sigma_{22}-\sigma_{12}^2}{2\sigma_{11}}\right)\end{aligned}$$

Thus, the condition for the choice of the metered plan is

(12) $$\exp\left(\eta_{it}\left(1+\frac{\sigma_{12}}{\sigma_{11}}\right)\right)<\frac{\left(f^F-f^M\right)\beta}{\left[1-\exp\left(-\beta p_t^M\right)\right]\exp\left(\alpha_i+\gamma Z_{it}+\frac{\sigma_{11}\sigma_{22}-\sigma_{12}^2}{2\sigma_{11}}\right)}$$

(13) $$\Rightarrow\eta_{it}<\frac{\sigma_{11}}{\sigma_{11}+\sigma_{12}}\ln\left[\frac{\left(f^F-f^M\right)\beta}{\left[1-\exp\left(-\beta p_t^M\right)\right]\exp\left(\alpha_i+\gamma Z_{it}+\frac{\sigma_{11}\sigma_{22}-\sigma_{12}^2}{2\sigma_{11}}\right)}\right]$$

Define

(14) $$\overline{\eta}_{it}=\frac{\sigma_{11}}{\sigma_{11}+\sigma_{12}}\ln\left[\frac{\left(f^F-f^M\right)\beta}{\left[1-\exp\left(-\beta p_t^M\right)\right]\exp\left(\alpha_i+\gamma Z_{it}\right)\exp\left(\frac{\sigma_{11}\sigma_{22}-\sigma_{12}^2}{2\sigma_{11}}\right)}\right]$$

Thus, if $\eta_{it}<\overline{\eta}_{it}$, the consumer chooses the metered plan; otherwise, she chooses the fixed plan.

2.1.2 Usage Decision

After the plan is chosen, the value of ν_{it} is revealed to the consumer and she decides how much to use the local phone service. The demand function (i.e. usage of the phone service) can be derived from the indirect utility function using Roy's identity.

$$x_{it} = \frac{-\frac{\partial V_{it}}{\partial p_t}}{\frac{\partial V_{it}}{\partial y}} \tag{15}$$

Thus, if the metered plan is chosen, the demand is given by

$$x_{it}^M = \theta_{it} \exp\left(-\beta p_t^M\right) \tag{16}$$

and if the fixed plan is chosen, the usage is given by

$$x_{it}^F = \theta_{it} \tag{17}$$

Taking logs and using (2), we get the demand expressions for metered and fixed plans respectively as

$$\ln\left(x_{it}^M\right) = \alpha_i + \gamma Z_{it} + \eta_{it} - \beta p_t^M + \nu_{it} \tag{18}$$

$$\ln\left(x_{it}^F\right) = \alpha_i + \gamma Z_{it} + \eta_{it} + \nu_{it} \tag{19}$$

2.2 Learning Models

In the base model, we assumed that consumers are informed about everything except ν_{it} at the time they make their plan choice decision. In particular, they know their choice shock - η_{it}, their type α_i and all parameters that do not vary with individual - β and γ. Thus, they are fully informed about everything except the realization of the usage shock ν_{it}.

However, consumers may be uncertain even about their type α_i. Before this tariff experiment, all users were on the fixed-rate plan. Typical telephone bills for fixed-rate plans do not give details on usage. Further, since there are no consequences of varying the level of usage, consumers are unlikely to pay much attention to their usage as long as they are on a fixed plan and do not have any option of switching to any other plan. Thus, it is plausible that they are uncertain about their mean usage. Since there is a one to one correspondence between mean usage levels and type α_i (see equations (18) and (19) to see why), uncertainty about mean usage also implies uncertainty about type. Consumers may thus have some belief about their type and may learn about their true type through the usage experience. If such learning takes place, consumers whose telephone bills under the measured plans are higher than what they would have paid under the fixed plan are more likely to switch back to the fixed plan than consumers who have a lower bill than the fixed plan charges. Miravete (2002) presents some reduced-form evidence for this kind of learning and finds that consumers do appear to respond to even small savings opportunities.

We specify and estimate two alternative learning specifications that build on the base model presented earlier. We refer to the two models as the "Constrained Learning Model" and the "Unconstrained Learning Model", and describe in Sections 2.3 and 2.4 respectively. The main difference between the two learning models is in the nature of information that is received by the consumers. In the constrained learning model in section 2.3, we make the assumption that the information received by the consumers is their usage level, seen by them in their telephone bill. Thus, there is a direct relationship between their usage levels and the realization of the signals they receive. Only measured plan consumers are assumed to update their belief about their type. In the unconstrained learning model in section 2.4, on the other hand, we are agnostic about the precise source of information received by the consumers. We make the assumption that unbiased signals are received by consumers about their types every month, with different variances of these signals for fixed and measured plan consumers reflecting the different information content in these two types of plans.

2.3 Constrained Learning Model

In order to incorporate learning by consumers on measured plans, we need to make a further assumption about the consumer behavior in this category. Suppose consumers know everything except α_i when they see their telephone bill, and in particular if they know the value of ν_{it} at this time (recall that consumers do not observe ν_{it} only at the time of plan choice), they could compute their α_i deterministically after just one period of measured plan usage. To see this, refer to equations (18). Given x_{it}^M and all parameters on the right hand side except α_i, computing α_i is trivial. By contrast, here we assume that what is revealed to consumers at the time of usage is $\alpha_i + \nu_{it}$ and not the separate components. At the end of the month, each consumer on the measured rate plan then updates her belief about her true type using this information on her usage. On the other hand, fixed plan users, who do not receive any information on their usage, are assumed not to update their beliefs. We refer to this model as the 'constrained learning model' because (a) we assume that consumers in the fixed plan do not learn their type α_i at all through their usage since their telephone bills are uninformative about usage, and (b) we assume that for measured plan consumers, the amount of usage reflected in their telephone bills are used by them to infer their true type α_i. This is in contrast to the 'unconstrained learning model' discussed in Section 2.4 later, where we relax these assumptions.

To model learning, we assume that the consumers have a belief about α_i in each period. In order to indicate that this belief for α_i is stochastic from the point of view of the consumer, we shall henceforth denote this belief as $\tilde{\alpha}_i$, to differentiate this belief from the true type α_i. This belief is assumed to be distributed normally as

(20) $$\tilde{\alpha}_i \sim N\left(\alpha_{it}, \sigma_{it}^2\right)$$

Note that the true type is not time varying, but the belief about this type does depend on the information set I_{it} of consumer *i* at time *t*, and hence its mean α_{it} and variance σ_{it}^2 are time varying.

We assume that consumers update their beliefs in a Bayesian manner, i.e. in each period they use their prior beliefs and information they receive from observing their own usage and apply Bayes Rule to compute their posterior belief. This posterior belief is used in the decision process in the next period. Further, this posterior belief becomes the prior belief at the next occasion when the belief is updated.

The initial belief of all consumers at the beginning of the tariff experiment (i.e. at the beginning of the first period) is assumed to be

(21) $$\tilde{\alpha}_{i0} \sim N\left(\alpha_{i0}, \sigma_{\alpha_0}^2\right)$$

where its mean in turn is drawn from the true distribution of types across the population, which we assume to be normal.

(22) $$\alpha_{i0} \sim N\left(\alpha, \sigma_{\alpha}^2\right)$$

$\sigma_{\alpha_0}^2$ has to be fixed to 1 for identification purposes

The consumer of the measured plan knows her usage x_{it}^M, her demographic characteristics Z_{it}, price p_t^M, choice shock η_{it} and coefficients γ and β. Additionally, she knows the covariance matrix of the errors Σ. She does not know her true type α_i or the realization of the usage shock ν_{it}. She however knows that conditional on η_{it}, the distribution of $\nu_{it} \mid \eta_{it}$ must be the distribution in (10).

Thus, she infers that

$$(23) \qquad \left(\alpha_i + \nu_{it}\right) \mid \eta_{it} \sim N\left(\alpha_i + \frac{\sigma_{12}\eta_{it}}{\sigma_{11}}, \frac{\sigma_{11}\sigma_{22} - \sigma_{12}^2}{\sigma_{11}}\right)$$

She knows in turn that

$$(24) \qquad \alpha_i + \nu_{it} = \log\left(x_{it}^M\right) - \gamma Z_{it} + \beta p_t^M - \eta_{it}$$

Denote

$$(25) \qquad s_{it} = \log\left(x_{it}^M\right) - \gamma Z_{it} + \beta p_t^M - \eta_{it}\left(1 + \frac{\sigma_{12}}{\sigma_{11}}\right)$$

From (23), (24) and (25), the consumer knows that

$$(26) \qquad s_{it} \sim N\left(\alpha_i, \frac{\sigma_{11}\sigma_{22} - \sigma_{12}^2}{\sigma_{11}}\right)$$

s_{it}, whose mean is her type, α_i, is thus a signal of this type. The consumer knows the realization s_{it} of this distribution and its variance $\frac{\sigma_{11}\sigma_{22} - \sigma_{12}^2}{\sigma_{11}}$, but not the mean. She thus updates her belief about her type using Bayes Rule, by combining her prior belief with the information contained in s_{it} and obtains the posterior belief about α_i. Since the prior belief is normally distributed, and the signal is also normally distributed, the self-conjugacy of the normal distribution ensures that the posterior is also normally distributed. In fact, it can be shown that the posterior distribution is $N\left(\alpha_{i(t+1)}, \sigma_{i(t+1)}^2\right)$, where

(27) $$\alpha_{i(t+1)} = \frac{\dfrac{\alpha_{it}}{\sigma_{it}^2} + \dfrac{\sigma_{11} s_{it}}{\sigma_{11}\sigma_{22} - \sigma_{12}^2}}{\dfrac{1}{\sigma_{it}^2} + \dfrac{\sigma_{11}}{\sigma_{11}\sigma_{22} - \sigma_{12}^2}}, \text{ and}$$

(28) $$\sigma_{i(t+1)}^2 = \frac{1}{\dfrac{1}{\sigma_{it}^2} + \dfrac{\sigma_{11}}{\sigma_{11}\sigma_{22} - \sigma_{12}^2}}$$

If the consumer is on a fixed plan, on the other hand, there is no updating of the belief and hence $\alpha_{i(t+1)} = \alpha_{it}$ and $\sigma_{i(t+1)}^2 = \sigma_{it}^2$.

Note that this model differs somewhat from typical learning models (Erdem and Keane 1996), in that the variance of the information signal (s_{it}) is not a separate parameter to be estimated, but is a function of the components of Σ. This implies that the rate of learning (which depends on the variance of the information signal) is a function of the variance of the choice and usage shocks.

The plan choice shock η_{it} of the consumer and the usage shock ν_{it} are assumed to be jointly distributed as in the base model

$$\begin{pmatrix} \eta_{it} \\ \nu_{it} \end{pmatrix} \sim N(0, \Sigma)$$

where $$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix}$$

Since consumers are uncertain about their type, they are also uncertain about their utility as a consequence. The conditional indirect utility function is therefore given as

(29) $$\tilde{V}_{it}^M = \left(y_i - f^M\right) + \frac{\tilde{\theta}_{it}}{\beta}\exp\left(-\beta p_t^M\right)$$

(30) $$\tilde{V}_{it}^F = \left(y_i - f^F\right) + \frac{\tilde{\theta}_{it}}{\beta}$$

where

(31) $$\ln\left(\tilde{\theta}_{it}\right) = \tilde{\alpha}_i + \gamma Z_{it} + \eta_{it} + \nu_{it}$$

We make the assumption that the consumer is an expected utility maximizer. The condition for the choice of the measured plan remains similar to the one for the base model. Specifically, the measured plan is chosen if

(32) $$E\left[\tilde{V}_{it}^{M}\right] > E\left[\tilde{V}_{it}^{F}\right]$$

Otherwise, the fixed plan is chosen. This gives us the following condition:

(33) $$n_{it} < \frac{\sigma_{11}}{\sigma_{11} + \sigma_{12}} \ln\left(\frac{\left(f^F - f^M\right)\beta}{\left[1 - \exp\left(-\beta p_t^M\right)\right] \exp\left(\alpha_{it} + \gamma Z_{it} + \frac{\sigma_{11}\sigma_{22} - \sigma_{12}^2}{2\sigma_{11}} + \frac{\sigma_{\alpha_{it}}^2}{2} \right)} \right)$$

Define

(34) $$\overline{\eta}_{it} = \frac{\sigma_{11}}{\sigma_{11} + \sigma_{12}} \ln\left(\frac{\left(f^F - f^M\right)\beta}{\left[1 - \exp\left(-\beta p_t^M\right)\right] \exp\left(\alpha_{it} + \gamma Z_{it} + \frac{\sigma_{11}\sigma_{22} - \sigma_{12}^2}{2\sigma_{11}} + \frac{\sigma_{\alpha_{it}}^2}{2} \right)} \right)$$

Thus, the measured plan is chosen if $\eta_{it} < \overline{\eta}_{it}$, else the fixed plan is chosen.

In order to obtain the usage equations, we again apply Roy's identity as before,

(35) $$\ln\left(x_{it}^{M}\right) = \tilde{\alpha}_i + \gamma Z_{it} + \eta_{it} - \beta p_t^M + \nu_{it}$$

(36) $$\ln\left(x_{it}^{F}\right) = \tilde{\alpha}_i + \gamma Z_{it} + \eta_{it} + \nu_{it}$$

It would be important to note at this stage that through this learning process, we incorporate a specific form of state dependence in the model. If we were interested in accounting for state dependence while being agnostic about the process through which this state dependence occurs, an alternative method would be to include serially correlated shocks in the base model. However, our learning specification tells us something about the process through which this state dependence occurs in a parsimonious way. Since it is a situation where consumers are new to the calling plan, learning is a natural means through which consumers' decisions could be state dependent.

An important point to note in this model is that the realization of the signal s_{it} depends on η_{it}, which is unobserved to the researcher (though observed by the consumer). While integrating out this unobserved signal distribution, we need to be conscious of the fact that conditional on having chosen the measured plan, η_{it} is not normally distributed. Rather, it is a truncated normal, with an upper truncation at $\bar{\eta}_{it}$. This needs to be accounted for when integrating out the distribution of signals.

2.4 Unconstrained Learning Model

In the model of learning above, we made the assumption that only measured plan users learnt about their true type α_i and that fixed plan users do not learn at all. Furthermore, we made the assumption that while the consumer observes $(\alpha_i + \nu_{it})$ perfectly, she is not able to separate α_i from ν_{it}. But it may be the case that both these assumptions are not valid. Fixed plan users may learn about their type, even though they do not see their usage in their telephone bills, because they may observe their own usage, albeit imperfectly. Furthermore, even measured plan users use sources other than the telephone bill alone to learn about their mean usage. In order to account for such possibilities, while being agnostic about the sources of information for fixed and measured plan users, we develop an alternative model of learning, which we now describe.

To allow for information to be received by both fixed and measured plan users, we make the assumption that both fixed plan and measured plan users receive unbiased signals about their true type. The implication of the signals being unbiased is that the mean of the signals is the true type of the consumers.

The information that the consumer receives from the telephone bill is assumed to be a normally distributed signal. Further, we assume that the signal received if the consumer is on the fixed plan is inherently different from the signal received if she is on the measured plan. This reflects the fact that for the measured rate plan, the telephone bill itself contains information about usage while the fixed rate plan has no explicit information about usage in the telephone bill. We expect to find that the variance of the signal in the case of the measured plan is much lower than in the case of the fixed plan because of this reason (though we do not make any *a priori* assumption about this). The signals for the measured rate plan are given as

(37) $$s_{itM} \sim N\left(\alpha_i, \sigma_{sM}^2\right)$$

and for the fixed rate plan as

(38) $$s_{itF} \sim N\left(\alpha_i, \sigma_{sF}^2\right)$$

Applying Bayes Rule, the belief at time *(t+1)* is given by

(39) $$\tilde{\alpha}_i \sim N\left(\alpha_{i(t+1)}, \sigma_{i(t+1)}^2\right)$$

where

(40) $$\frac{1}{\sigma_{i(t+1)}^2} = \frac{1}{\sigma_{it}^2} + \frac{1(Fixed_{it})}{\sigma_{sF}^2} + \frac{1(Meas_{it})}{\sigma_{sM}^2}$$

and

(41) $$\alpha_{i(t+1)} = \sigma_{i(t+1)}^2 \left(\frac{\alpha_{it}}{\sigma_{it}^2} + \frac{s_{itF}\,1(Fixed_{it})}{\sigma_{sF}^2} + \frac{s_{itF}\,1(Meas_{it})}{\sigma_{sM}^2} \right)$$

$1(Fixed_{it})$ and $1(Meas_{it})$ are indicator variables that take the value 1 if the chosen plan for consumer *i* at time *t* is fixed or measured respectively and zero otherwise. Only one of them can be 1 for a particular consumer at a particular time.

In order to complete the learning specification, we need to specify a belief at the first period. We make the same assumption here as in the constrained learning model, i.e. the assumptions in equations (21) and (22). The remaining assumptions are the same as those in the constrained learning model presented in section 2.2.

Figures (1) through (3) give a summary of what is observed by the consumers at each stage of the three models – choice decision stage, usage decision stage and belief updating stage.

3. Data

The data for this study are from the South Central Bell (SCB) local telephone service experiment run for the evaluation of the Kentucky Public Service Commission (KPSC) in 1986 in Louisville. SCB requested the KPSC for permission to introduce an optional measured calling plan in a market that had only a fixed calling plan for local telephone service. In order to first evaluate the effect of introducing the measured plan, the KPSC asked SCB to conduct a tariff experiment for two cities – Bowling Green and Louisville. The data we use in this study are from the experiment in Louisville.

In this experiment, extensive demographic information was collected for a panel of consumers. They were all on the fixed plan in the spring of 1986. The optional measured calling plan was introduced in July and their usage tracked for the three months of October, November and December. We have observations for a total of 1542 households for the months of October through December on the plan chosen (a fixed tariff plan vs. a measured plan) and their overall usage. The fixed rate plan allowed unlimited usage for $18.70 per month while the measured rate plan included a fixed fee of $14.02 and a per minute usage of effectively 4 cents a minute.[2]

Our data are for a choice-based sample and this needs to be accounted for in our empirical analysis. We explicitly correct for this biased sampling in our estimation procedure to get consistent estimates (Manski and Lerman 1977). This procedure involves weighting the likelihood contribution of each observation according to the population and sample distributions of fixed and measured plan consumers

Finally, we use only a subset of the full set of demographic variables in the analysis. These variables are chosen by estimating the simplest base model (without heterogeneity on the type of the consumer α) with the full set of demographic variables. We then used only those variables that were significant at the 90% level for all subsequent analysis. We report the estimation results for all the alternative models only for this restricted demographic variable set, so they are comparable. This was done essentially to keep estimation feasible.

An important aspect of these data is that they are obtained in an experimental setting, with the experiment being conducted by a public regulator. Thus, the usual concerns about endogeneity of prices do not hold in this context. The prices of the two plans were chosen exogenously and consumers were not assigned to specific plans or targeted with advertising for specific plans.

The summary statistics for the data used is given in Table 1. A full description of the data and more complete summary statistics for all the demographic variables can be seen in Miravete (2002). There are some additional features of the data that are important to our specific modeling context. From Table 1, it is clear that the number of consumers in the two plans is very

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[2] The actual tariff was much more complicated with the presence of setup costs and time and distance bands. However, for the sake of simplicity of exposition, we considered the weighted average price of $0.04 per minute.

similar in the three months for which we have data and therefore, it might appear as if there is no switching. However, there is some level of switching in this data, and it is greater than what it might appear in Table 1, though its magnitude is indeed small. In all, there are 44 consumers in our data who switch from fixed to the measured plan and 46 who switch from measured to fixed plans. Since these happen simultaneously, the total number of consumers in the two plans remains almost the same across the three months.

We also briefly discuss the degree of *ex-post* mistakes made by consumers in this dataset since that is an important feature of this market that our model captures. First, note that given fixed fees of $14.20 and $18.00 for the measured and fixed plan respectively and marginal price of $0.04 per minute for the measured plan, the measured plan is optimal for usage below 95 minutes, while the fixed plan is optimal above that usage. In the dataset, there are totally 1342 consumer-month combinations for the measured plan, of which 1055 have usage greater than 95 minutes. For the fixed plan, 147 out of a total of 3284 had usage below 95 minutes. Thus, there were a large number of *ex-post* mistakes in the dataset, with a greater proportion for measured plan users.

4. Estimation

4.1 Base Model (without learning)

In typical two-stage estimation of discrete/continuous models, there is a potential endogeneity bias between the error in the quantity (usage) equation and the dummy for choice. However, we do not face this problem as we characterize the joint distribution of the parameter that affects choice (η_{it}) and the error (ν_{it}). Hence, the likelihood already accounts for this correlation and there is no inconsistency in our estimates. In typical two-stage estimation problems, the researcher is unable to or unwilling to characterize the joint distribution of these potentially correlated factors and hence the need to correct for endogeneity.

Equations (13), (18) and (19), coupled with the distributional assumptions for η_{it} and ν_{it} in (2) allow us to specify the likelihood for a consumer *i* at time t as follows

(42)
$$L_{it} = \left[\int_{-\infty}^{\bar{\eta}_i} \phi_{\nu|\eta} \left(\ln(x_{it}) - \eta_i - \alpha_i - \gamma Z_{it} + \beta p_t^M \right) d\eta_{it} \right]^{I_{it}^M} \left[\int_{\bar{\eta}_i}^{\infty} \phi_{\nu|\eta} \left(\ln(x_{it}) - \eta_{it} - \alpha_i - \gamma Z_{it} \right) d\eta_{it} \right]^{\left(1-I_{it}^M\right)}$$

where

I_{it}^M is the indicator variable that takes the value 1 if the metered plan is chosen

$\phi_{\nu|\eta}$ is the p.d.f. of the distribution of $\nu_{it} \mid \eta_{it}$ (which was derived earlier in 10)

The likelihood for individual i is evaluated by integrating this over the unobserved distribution of types α_i

(43)
$$L_i = \int \prod_{t=1}^{T} L_{it} d\alpha_i$$

The type α_i is distributed normally as

(44)
$$\alpha_i \sim N\left(\alpha, \sigma_\alpha^2\right)$$

The overall likelihood is given by

(45)
$$L = \prod_{i=1}^{N} L_i$$

The integral in the likelihood expression in equation (42) is hard to evaluate analytically. Hence, it has to be computed numerically. In this case, it is cumbersome to use simulation methods to numerically evaluate this integral, especially when the limits of these integrals are in the tails of the distribution of η_{it}. This is because there are few draws to the left of or right of this of the limit $\bar{\eta}_i$ as the case may be and the simulation error would be unacceptably high.

Hence, we evaluate these integrals numerically using Gaussian quadratures. We used numerical integration for the integral in (40) as well. A maximum likelihood procedure written in Matlab was used for the estimation.

4.2 Models with learning

The likelihood functions in the models with learning are a slight modification of the one in equation (42).

$$(46)\qquad L_{it} \mid \tilde{\alpha}_i = \left[\int_{-\infty}^{\bar{\eta}_{it}} \phi_{\nu|\eta}\Big(\ln(x_{it}) - \eta_{it} - \tilde{\alpha}_i - \gamma Z_{it} + \beta p_t^M\Big) d\eta_{it}\right]^{I_{it}^M} \left[\int_{\bar{\eta}_{it}}^{\infty} \phi_{\nu|\eta}\Big(\ln(x_{it}) - \eta_{it} - \tilde{\alpha}_i - \gamma Z_{it}\Big) d\eta_{it}\right]^{\left(1 - I_{it}^M\right)}$$

$$(47)\qquad L_i = \int \prod_{t=1}^{T} \Big(L_{it} \mid \tilde{\alpha}_i\Big) d\tilde{\alpha}_i$$

(noting that the distributions of $\tilde{\alpha}_i$ for a specific consumer *i* differ for different periods though they are interrelated through the learning process).

The overall likelihood is again

$$(48)\qquad L = \prod_{i=1}^{N} L_i$$

4.3 Empirical Specification

For the empirical analysis, we need to specify the variables that would be included in Z_{it}. The variables include a set of demographic variables for the consumers and also a set of month dummies to capture any systematic variation from month to month. The set of demographic variables is similar to that in Miravete (2002) and includes those demographic characteristics that can be expected to affect telephone usage. They include the size of the household, number of teens in the household, whether the head of the household is college educated, and whether he/she has received federal/local benefits. We also include month dummies for the months of November and December (with the data running from October to December). Since the variance-covariance matrix Σ needs to be a positive definite matrix, we reparametrize it in terms of its Cholesky roots. Since the parameters β (note that that $-\beta$ plays the role of the price coefficient) and the learning signal variances are all constrained to be greater than 0, we re-parameterize them as $\beta = \exp(b)$; $\sigma^2_{sF} = \exp(s_{sF})$ and $\sigma^2_{sM} = \exp(s_{sM})$.

5. Identification

5.1 Base Model

Since there is only one price that does not vary over time, it may appear that a price coefficient cannot be identified. However, what identifies the price coefficient is the fact that for consumers who switch from measured to fixed plan or vice versa at least once, we observe different usage levels. Thus, while there is no price variation within a kind of plan, we do observe price variation across plans (zero for the fixed plan and p_t^M for the measured plan). This allows us to estimate the price coefficient.

The γ parameters are identified from the systematic differences in usage across different types of consumers with different demographics. The heterogeneity in α_i is identified through the variation in usage across consumers.

We next discuss the identification of the variance parameters (σ_{11}, σ_{22} and σ_{12}). It may be counterintuitive that a full covariance matrix can be identified and hence we lay out the intuition of the non-parametric identification of these parameters, beyond the functional form identification through non-linearity. Imagine there only being the usage equation. In that case, the variance of the usage regression (the equivalent of σ_{22}) would be identified trivially. Now, note that we have two different types of usage equations for the two different types of plans. There are thus two different variances that could be identified if the two usage regressions were independently estimated. However, in our case, we have the same set of parameters for both regressions. Different variances for the users of the two plans comes about by the fact that although the marginal distribution of ν_{it} is the same for customers of both plans, the distribution of ν_{it} conditional on η_{it} is not. Thus, the degree to which variance in the usage of the two plans differs systematically identifies the other two parameters of the covariance matrix. Another piece of information that feeds into the identification of these parameters is the degree to which heavy users choose fixed plans and the extent of ex-ante mistakes.

5.2 Constrained Learning Model

In the case of the constrained learning model, there are no additional parameters to be estimated. However, it must be noted that the model places some additional restrictions on the parameters over and above those in the base model. The signal variance in the constrained learning model is a function of the variances of the choice and usage shocks and the covariances between them. Thus, the identification of these variances and the covariance depends not just on the arguments presented in section 5.1 above, but also on the dependence in choices between periods. Specifically, the rate at which consumers switch out of the measured plan after discovering that their usage is high helps identify these variances.

5.3 Unconstrained Learning Model

In the case of the unconstrained learning model, the additional parameters to be estimated apart from those in the base model are the variances of the learning signals for the fixed and measured plans. The identification of the variance for the measured plan, for instance, depends on the extent to which people switch back to fixed rate plan from the measured rate plan after they discover that their usage is high. A similar argument holds for fixed rate plans as well, with the difference being that consumers switch out of the plan when they discover their usage to be too low to justify being on the fixed plan. Miravete (2002), who uses similar data as we do, finds evidence for such switching by consumers in order to save costs. He also finds that there is a greater degree of switching from measured rate service to fixed rate service in response to potential savings than the other way round.

A high variance of the usage signal in our model would suggest that learning is slow and a low variance would suggest relatively fast learning. This can be seen from equations 24 and 25, where the prior belief and usage signal are weighted respectively by the reciprocals of the prior variance and variance of the usage signal. If the usage signal variance is high, relatively high weightage is given to the prior belief and less to the signal and vice versa. Thus, the extent to which consumers switch as a result of observing their own *ex-post* mistakes would tell us about the pace of learning and hence about these learning variances. Specifically, if we find that consumers switch faster from the measured rate plan to the fixed rate plan, we would find that the signal variances for the measured plan would be lower than that for the fixed-rate plan.

6. Results

Table 2 gives the parameter estimates for four sets of models. In the first model (henceforth referred to as the *homogeneous model*), we assume consumers to be homogeneous in their type α_i but consumers are assumed to know this type with certainty. In the second model (henceforth *heterogeneous model*), we allowed consumers to be heterogeneous in their types, again with consumers knowing this type with certainty. In the third model (*constrained learning model*), we allow for consumer uncertainty about their type and model the process of learning about this type through their own usage experience for measured plan consumers. In the fourth model (*unconstrained learning model*), we allow for consumers of both fixed plans and measured plans to learn about their type, through information signals whose sources we are agnostic about.

We find that in all models, the β parameters are statistically significantly different from zero, indicating that changes in prices would cause consumers to switch between plans and adjust their usage. That price coefficients in the case of the homogeneous, heterogeneous and constrained learning model and unconstrained learning model are respectively -4.3403 x 10^{-4}, -4.3877 x 10^{-4}, -4.4134 x 10^{-4} and -3.3412 x 10^{-4}. These results are consistent with the findings of Miravete (2002) who finds that consumers switch between plans to obtain small cost savings. Since the magnitude of the price coefficient does not have an intuitive meaning, we shall investigate the price effect in more detail later in this section.

Most of the demographic variables, including household size, the number of teens in the household and whether the household received federal and local benefits are also significant and of the expected sign. The dummy variables for the months of November and December are also significant. The magnitudes of signs of these coefficients indicate that usage in December is systematically higher than that in November but usage in both these months is lower than that in October.

In all four models, the variance of the plan choice shock is greater than that of the usage shock. For instance, in the homogenous model, the variance of the plan choice shock is 0.6012 while that for the usage shock is 0.3980 (these numbers are obtained by converting the Cholesky root in Table 2 into the variance covariance matrix). The plan choice shock has greater variance than the usage shock in the case of the other models as well. Importantly, these parameters are mostly significant at the 95% level and at least at the 90% significance level. The variance of the usage shock is considerably lower for the constrained learning model (but not for the unconstrained learning model). One reason for this difference is that the signal variance is related to the variances of the shocks and hence switching behavior informs us about the variances of the shocks in the constrained learning model.

In the heterogeneous model, the additional parameter estimated is the variance parameter for heterogeneity on the type of consumers (α_i). The point estimate of this variance is 0.6735 and it is significant. It is interesting to compare this variance with the plan choice shock variance of 0.2364 and a usage shock variance of 0.0737 for the same model. It suggests that there is a significant amount of heterogeneity amongst consumers in terms of their mean usage and this variance is much greater than that for the plan-choice shock and usage shock. Further, the log-likelihood at the estimated parameters for the heterogeneous model is significantly improved compared to the homogeneous model. This suggests that accounting for heterogeneity is important and can better explain the variation in plan choice and usage in the data.

In the third model, we add consumer learning about their type for measured plan consumers, to the heterogeneous model. While there are no additional parameters to be estimated, we have an additional interpretation of the variance parameters. Specifically, from equation (26), the variance of the signal s_{it} is given by $\frac{\sigma_{11}\sigma_{22} - \sigma_{12}^2}{\sigma_{11}}$. Thus, from table 2, we get this variance as 7.1118 x 10^{-4}.

In the unconstrained learning model, we estimate additional signal variance parameters to account for learning of their types by consumers of both fixed and measured plans. Our expectation was that consumers learn about their own mean usage through their own experience and switch plans if they find that they would be better off under the alternative plan. Further, consumers of the measured plan are likely to learn about their mistakes much more quickly than those in the fixed plan. Firstly, the telephone bill for measured plan consumers contains details about usage that are not in the telephone bill for fixed plan consumers. Further, any mistake made by the measured plan consumer is easily discovered by the fact that the telephone bill amount is greater than that for the fixed-rate plan. For consumers on the fixed rate plan, a mistake would suggest that they could have saved money if they were on the measured plan. This is much more difficult for consumers to become aware of, unless they are conscious of their usage. Thus, we expect the measured plan consumers to learn about their usage faster than those on the fixed plan. Miravete (2002) provides some evidence to support this expectation.

Table 2 gives the additional parameters for the unconstrained learning model that we use to investigate this issue. Specifically, there are two additional parameters in the case of this model – the learning signal variances for the measured rate and fixed rate plan. The estimated signal variance in the case of the measured rate plan is 1.1318×10^{-4} whereas that for the fixed rate plan is 5.2859×10^{3}. Note that the estimated signal variance for measured plans in this unconstrained learning model is in the same order of magnitude as that for the constrained learning model presented earlier. The point estimates for these parameters support our expectation that consumers learn much faster if they are on the measured rate plan than if they are on the fixed rate plan. These numbers suggest that on average, consumers' uncertainty about their usage reduces to less than 10% of the initial value in less than one month in the case of the measured rate plan. On the other hand, this variance does not reduce to 10% of its initial value even after 100 months in the case of the fixed rate plan. While these numbers themselves may suggest an extreme degree of dichotomy in learning for the two types of plans, what is interesting is the directional result, that consumers learn faster if they are on the measured plan. Note also that all consumers were on the fixed plan before the tariff experiment. Thus, consumers who continued on the fixed plan would be unlikely to learn any new information of their mean usage levels. Furthermore, the telephone bill for the fixed plan users did not have information on their usage levels. Thus, the slow learning results for the fixed plan are along expected lines.

An important decision variable for firms in the industry is the pricing of the plans. In order to do this in a systematic manner, firms need estimates of price elasticities of demand in the case of optional calling plans. In the situation where prices affect both plan choice and usage of the local telephone service, it would be useful to see how prices affect both of these outcomes. We thus computed two separate elasticities of demand and have reported them in Table 3. The usage elasticity reported in this table measures the percentage change in usage across all measured plan consumers if prices were raised by 1%. The choice elasticity measures the % change in choice probability of choosing the measured plan if prices were raised by 1%. These elasticities were computed by simulating the expected usage and choice probability under existing prices and then again simulating these variables under the counterfactual situation that prices were raised by 1%.

In the case of the homogeneous model, we find that the usage elasticity for the measured plan is -2.7453, whereas the choice elasticity for the measured plan is -1.8130. In the case of the heterogeneous model, these elasticities are lower at -1.7582 and -1.0305 respectively. The addition of heterogeneity considerably reduces the price elasticities, suggesting that accounting for heterogeneity is important when we look at the pricing decision too. When we ignore heterogeneity, we are disregarding the self-selection of consumers to different plans based on their mean usage levels and hence overestimate the price effect. The elasticities for the constrained learning model are similar in magnitude to those for the heterogeneous model – -1.8311 and -1.0492 respectively and for the unconstrained learning model, they are -1.9241 and -

1.0631 respectively. Overall, all these elasticities are significantly higher than those reported in prior research (for instance, Park, Wetzel and Mitchell 1981), suggesting that consumers are relatively price elastic and firms' margins are more moderate than in earlier estimates. These price elasticities are also more consistent with monopoly pricing than the elasticities reported in previous studies.

The most significant feature of our model is that we incorporate consumer uncertainty to account for differences between *ex ante* and *ex post* optimal choices. A natural question to ask therefore is the implication of this uncertainty on consumers. In order to answer this question, we conduct a set of counterfactual simulations to estimate the value of information in this context.

There are potentially two levels of consumer uncertainty in our model. First, the consumer is uncertain about the realization of the usage shock at the time of plan choice. Second, the consumer is uncertain about her type (which translates to uncertainty about her mean usage). Both these levels of uncertainty could lead to a potentially suboptimal plan choice. We define the value of information to the consumer as the amount of money the consumer would be willing to pay to obtain a specific piece of information. In line with previous literature on the value of information (Chernew, Gowrisankaran and Scanlon 2006; Jin and Sorensen 2005), this is operationalized as the compensating variation for the two scenarios – with and without information, i.e. the income compensation to the consumer that would equate the indirect utility of the optimal choice under the two scenarios.

As noted above, consumers have two levels of uncertainty in our model – about the choice shock and about their types. Thus, we compute two different measures of the value of information. The first measure, which we refer to as the value of *limited information* is the value to the consumer of being perfectly informed about her type, but not about her choice shock. The second measure, which we refer to as the value of *complete information* is the value to the consumer of being informed about both her type and her choice shock. Limited information could be potentially conveyed to the consumer by the telephone company, by giving her history of usage (which was not available to the consumers in our dataset). It may seem impossible that the consumer can be informed about her choice shock *ex ante*, but it is actually equivalent to a scenario where she makes a choice after the choice shock is revealed. This could be practically implemented by the firm by providing the option to the consumer to switch plans at any time during the month or to commit to bill the consumer according to the ex-post optimal plan[3]. Thus, these measures of the value of information could be interesting to policy makers, in understanding the value to consumers of forcing telephone service providers to share information with consumers about their usage patterns, as well as forcing them to allow consumers to switch plans during the course of the month. This value of information could be compared to the marginal cost of implementing these policies to see if they provide net welfare benefits or not.

We now describe how we conduct these counterfactual experiments, by illustrating the procedure for the limited information case and using the estimates of the unconstrained learning model. We first simulate the choice shock (η_{it}) and usage shocks (ν_{it}) for every consumer for every time period and also their types (α_i) by drawing from their estimated distributions. We then used the parameter estimates of the constrained learning model to simulate the optimal plan choice for each consumer for each time period under the scenario where they are uninformed about both their choice shocks and their type. They thus integrate out the distributions of mean type and usage shock. Note that there are analytical expressions for these integrals and hence

[3] Note that the commitment to bill a consumer according to the ex-post optimal plan is not perfectly equivalent to revealing the choice shock ex-ante, since the consumer's usage is endogenous and is not independent of plan choice.

this integration need not be done numerically. We compute the indirect utility derived from this choice. We then repeat this simulation (using the same set of draws for the two shocks and of the mean type), but instead of integrating out the type distribution, we now assume that consumers know their specific mean type. Thus, for each draw of mean type for each consumer-month combination, we compute the optimal choice and corresponding indirect utility. We then compute the difference between these indirect utilities derived in the two scenarios – with information and without information about the consumer types. Since the marginal utility of income is 1 in our case, this difference in utilities is equal to its dollar value. We take the mean of this dollar value of difference in utilities across draws, across consumers and across time to obtain the value of *limited information*. A similar value of information is computed using the estimates of the constrained learning model. We similarly compute the value of complete information (i.e. about both the consumer type and usage shock) by simulating the indirect utilities under the scenarios where choices are made with and without information about both choice shock and type. Since the choice shock is uncertain even in the homogenous and heterogeneous models without learning, we compute the value of complete information using the estimates of these models as well.

The results of this set of counterfactual simulations are reported in Table 4. We find that the value of complete information to the consumer is relatively modest. The estimates for the two learning models and the heterogeneous model imply a value of complete information of between $0.4409 and 0.4610. The estimates of the homogeneous model suggest a lower value of information of $0.1873. Since these absolute numbers are not very meaningful, we compare them to the average value of the *ex-post* mistakes across consumers. We define the ex-post mistake as the difference between the amount paid by the consumer under the plan choice she actually made and the amount she would have paid under *ex-post* cost-minimizing plan, keeping her usage unchanged. If she chose her cost-minimizing plan, the mistake is equal to zero. The average value of mistakes by consumers in our dataset is $1.8133. The value of information therefore ranges about 25% of the average *ex-post* mistake for the learning models and heterogeneous model and about 10% for the homogenous model. Note that these two numbers are not directly comparable since the mistake is an *ex-post* measure, keeping usage unchanged. Also, this is the observation in the data. The value of information uses the model predictions using the estimated parameter values. Furthermore, the reason the value of information is lower than the ex-post mistake is that the marginal cost of usage does not enter the indirect utility function linearly.

The value of limited information for the constrained learning model is $0.3674 and for the unconstrained learning model is $0.4447. A comparison of the value of complete and limited information reflects the degree to which the two levels of uncertainty lead to choices that are suboptimal *ex-post*. We find that in both models, the value of limited information is close to the value of complete information. This suggests that a major proportion of the uncertainty is really that about type than about the choice shock. The value of limited information is almost equal to that for complete information in the unconstrained learning model case. This reflects the fact that the variance of the choice shock is very low relative to the variance in prior belief about type.

We do not explicitly compute the value of measured and fixed plans separately, since our estimates suggest that consumers learn very rapidly if they are on the measured plan but very slowly if they are on the fixed plan. As reported earlier in this section, the consumer uncertainty about type is reduced to 10% of its initial level in less than one month in the case of the measured plan and does not reduce to this level even after 100 months in the case of the fixed plan. Hence, the value of being on the measured plan is almost equal to the value of limited information, while that of the fixed plan is close to zero. We have verified that this is true, but do not report these numbers since they do not provide any significant additional information.

In order to look at the implications of the availability of optional calling plans for consumers and firms, we conducted some further counterfactual simulations. In the first simulation, we assessed the impact of the removal of one of the two calling plans on firms' expected revenues, consumer surplus and overall welfare. In order to compute the revenue impact, we sequentially removed the measured and fixed plan respectively and simulated the firm's expected revenues. These simulations used the estimates of the heterogeneous model. The computation of consumer surplus used the compensating variation approach (Small and Rosen 1981). The compensating variation is defined as the additional income that a consumer would need to be compensated by to provide her the same utility in the counterfactual situation as in the original situation. We compute this by finding the income difference that would equate the maximum indirect utilities under the two situations conditional on a particular draw of the unobservables and then integrating over the joint distribution of these unobservables. In our case, the unobservables are the type of the consumer (α_i) and the two shocks, the plan-choice shock (η_{it}) and the usage shock (ν_{it}).

Tables 5 and 6 give the revenue impact and consumer surplus of these counterfactuals respectively. We find that compared to the present scenario (i.e. the presence of both fixed and measured plans), the firm's revenues could go up by $7144.91 dollars for these 1542 consumers for all three months (i.e. $1.55 per consumer per month) if the measured plan were removed and only the fixed plan were present. Similarly, the firm could increase its revenues by $13175.26

($2.85 per consumer per month) if the fixed plan were removed. The difference in the revenue impact of the two scenarios reflects the fact consumers with high usage may end up paying very large sums of money if they had only the option of the measured plan. The loss in consumer surplus when the measured plan is removed is $30843.16, which translates to $6.67 per consumer per month, i.e. consumers would need to be compensated by this amount to keep them indifferent between the existing situation and the situation where the measured plan is no longer available to them. The compensating variation in the case of the removal of the fixed plan is even higher, at $27.37 per consumer per month. Thus, the overall welfare loss to society if the measured plan were removed is of the order of $5.12 per month and that of the removal of the fixed plan is $24.52 per consumer per month. The fact that the welfare loss is very high for the removal of the fixed plan reflects the fact that there is a large subset of users who have high usage of their local telephone service and would end up paying large sums of money if they had only the measured option, besides having to adjust their consumption of local telephone service.

We conducted two other simulations to study the impact of pricing on consumer surplus and the firm's revenues. In the first simulation, we find a tariff plan that would raise the firm's revenues, while keeping consumer surplus unchanged compared to the present scenario. In the second simulation, we find a tariff plan that would raise consumer surplus, even while keeping the firm's revenues unchanged. These two simulations may be interesting from the perspective of the firm and the public regulator respectively.

In both these counterfactual simulations, we kept the fixed plan unchanged, i.e. consumers still have the option of choosing a fixed plan that allows unlimited usage of their local telephone service for $18.70 per month. We varied the price (fixed and marginal) for only the measured plan for the purpose of these simulations. The results of the first simulation, reported in Table 7, suggest that if there were a measured plan option with a fixed fee of \$10.00 per month and per-minute usage charges of \$0.1062 (instead of the current option of \$14.02 a month and \$0.04 per minute of usage), consumer surplus at the aggregate level remains unchanged, but the firm can raise its revenues by \$6139.88. This amounts to \$1.32 per consumer per month. The results of the second simulation, reported in Table 8, shows that if there were a measured plan option with a fixed fee of \$16.00 and per-minute usage charges of \$0.0223, the firm's revenues would be unchanged, but consumer surplus would be increased by \$21462.16, i.e. \$4.64 per consumer per month. It is important to note that consumer surplus goes up in the aggregate in this second simulation (or remains unchanged at the aggregate level in the first simulation) compared to the existing scenario. It is not true that it goes up (or remains unchanged) for *every* consumer. In fact, there are consumers that are worse off under the new scenario, but their loss of surplus is compensated by the gain in surplus for other consumers.

7. Conclusion

We had the following objectives when we started this study. We set out to develop a model for the choice and usage of local telephone service that incorporated some specific features of such markets. First, there is self-selection in the decision to choose a specific plan. Consumers are likely to select the plan based on their usage levels. Second, there is a time lag between choice and usage. Consumers are uncertain about their future usage at the time they make their choice decision, but the extent of their usage would determine the price of the service. Hence, consumers commit to a particular plan before they know what the price of the plan would eventually be. Consumers regularly make mistakes, i.e. their ex-post price of the plan, given their actual usage, is higher than what it would have been under an alternate plan. Thirdly, consumers regularly switch between plans and do so to minimize their expected costs.

The model that we developed incorporates all these aspects of this market. We specifically allowed for self-selection of consumers into specific plans based on their usage levels, incorporated consumer uncertainty about actual usage level at the time of plan choice and in an enhancement to the model, allowed for consumer learning about their mean usage through their own usage experience. We estimated this model using data from the South Central Bell 1986 tariff pricing experiment.

We find that there is considerable heterogeneity across consumers in their mean usage levels. Consumers with high mean usage self-select into the fixed plan, while those with lower usage choose the measured plan. We find that demographic variables like household size, the number of teens in the household, whether the head of the household is college educated or not, and whether the household was receiving federal and local benefits have explanatory power usage levels and choice of plans.

An interesting finding of this study is that price has a significant effect on both choice of plan and usage of the measured plan. This provides evidence against the suggestion in some past studies that consumers do not respond to small changes in price. We find that price elasticities of choice and usage are both quite large compared to past research.

We measure the value of information to consumers about their type and the shock to their usage after they have made their plan choice. We find that the value of information to consumers is modest, and that a major proportion of this value is in information about their type, rather than in information about their usage shock.

We measure the impact of introduction of the optional measured plan compared to the pre-existing scenario where there was only a mandatory fixed rate plan. We find that there are substantial consumer gains due to the availability of the measured rate option compared to the pre-existing situation of mandatory fixed rate plan. Conversely, firms lose revenues due to the introduction of measured rate plans. Yet, overall welfare goes up, suggesting that society benefited due to the availability of the optional measured plan. While this result is to be expected, we are able to provide estimates about the extent of welfare gains due to the introduction of measured plan.

We also consider a second counterfactual scenario where there is only a mandatory measured rate plan and assess the impact of introduction of an optional fixed rate plan. We again find substantial gains in consumer surplus due to the availability of the optional fixed plan and losses in firm revenues. Both the gains in consumer surplus and losses in firm revenues are higher than in the earlier simulation where we compared a mandatory fixed rate regime with one where the measured plan was introduced. The overall welfare gains are much higher in the second counterfactual simulation than in the first. This suggests that in the market in our data, the welfare gains of introduction of a fixed plan when there is a mandatory measured plan are much higher than the gains due to introduction of a measured plan when there is only a mandatory fixed plan. This finding has important policy implications for the regulator.

We investigated the issue of consumer learning about their own mean usage. We find that consumers learn much faster if they are on the measured plan than if they are on the fixed plan. This is not a surprising result, considering that consumers get better details about their usage through their telephone bills if they are on the measured plan than if they are on the fixed plan. Further, consumers are more easily able to detect mistakes if they are on the fixed plan, since they would notice that their telephone bill is a higher amount than the fixed plan. To the contrary, a mistake in the fixed plan would imply that a consumer is using the telephone service less than the minimum quantity that would justify the fixed plan. However, since the telephone bill is a fixed quantity irrespective of usage, consumers would find it harder to judge if they made a mistake or not. Our results support such an explanation.

We finally conducted two simulations to demonstrate the effect of changing the fixed and marginal prices on the revenues of the firm and on consumer surplus. We show that the firm could significantly increase its revenues by offering to its consumers a different measured plan, even while keeping consumer surplus unchanged. Conversely, consumer surplus could significantly increase, even while the firm's revenues remained unchanged, if the firm offered a pricing schedule for the measured plan that was different from the current one.

It is also pertinent at this stage to talk about some of the limitations of this study. State dependence is allowed to enter our model only through the learning process. However, there may be state dependence due to other reasons, for instance, switching costs. We assume away any switching costs in our study. Switching costs are a potential explanation for stickiness in the tariff plan choice. Further, asymmetries in switching costs between fixed and measured plans may also potentially explain different degrees of stickiness between the two plans. Our hope is that because this tariff experiment did not have any explicit switching costs, any intangible switching costs that we ignore would not affect at least the directional nature of our results. We hope to address this in future work by explicitly accounting for state dependence in tariff plan choice. A further caveat regarding these asymmetries in stickiness is that consumers in fixed and measured plans in our dataset received differential information on usage. This situation may not prevail in other circumstances.

A second limitation, driven by the nature of the data, is that our model is conditional on choice of one of the two plans by the consumer. This is a reasonable specification, given our data, since almost all consumers were on the local telephone service, there was no competitor to South Central Bell and cellular telephones had not been widely adopted. However, in a more general situation, where there is an option to switch away from one provider to another, or to switch to a cellular telephone instead of a fixed-line phone, our model would need to be modified. A related issue is that our model is simple and tractable in the case where there are two tariff plan choices. While the model can be conceptually modified to accommodate more than two tariff plans, its estimation would become more challenging as the number of plans increases.

An assumption we make in the paper is that of the absence of switching cost. Relaxing this assumption is challenging in our modeling and data contexts, but could help answer several important questions about the inter-relationship between uncertainty and switching costs of consumers. Another assumption that may be worth investigating is that of risk-aversion of consumers. In our model, the degree of risk aversion is not estimated, but is a function of other parameters. If this were an estimated parameter, it might have been possible to investigate the interplay between risk aversion, uncertainty and learning in the choice of plans and stickiness to fixed vs. measured plans.

Distinguishing risk aversion from asymmetries in information between fixed and measured plans would be feasible given a longer time series than we have in our data. Both risk aversion and asymmetric learning might cause consumers to be sticky to fixed plans, even if it were suboptimal for them. However, the two explanations would differ in their implications for behavior of consumers who have already learned about their mean usage vs. those who have not.

Stickiness to fixed plans due to risk aversion would not differ based on how much consumers know about their usage levels. On the other hand, stickiness due to asymmetric information content would be very different for those who know a lot about their mean usage and those who don't. Consumers who have already learned about their mean usage, by being on a measured plan in the past for instance, are unlikely to remain on fixed plans even if it were suboptimal for them. Thus, systematic differences in switching behaviors for consumers who have ever been on measured plans in the past vs. those who have not would help distinguish the extent to which risk aversion and asymmetric information content explain stickiness to fixed plans. This would require observing consumers over a much longer period than the three months for which we have data. We thus leave the exploration of risk aversion vs. asymmetric information content to future research.

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Table 1: Summary Statistics

Variable	Plan		
	All	Flat	Measured
Number of Households – October	1542	1097	445
Number of Households – November	1542	1088	454
Number of Households - December	1542	1099	443
Usage	478.6402 (438.024)	575.8356 (469.872)	240.7941 (203.647)
Household Size	2.5603 (1.483)	2.7056 (1.496)	2.2022 (1.392)
Number of Teens in the household	0.2503 (0.636)	0.2963 (0.684)	0.1371 (0.481)
Head of the Household is college educated	0.2244 (0.417)	0.1841 (0.388)	0.3236 (0.468)
HH Receives Federal/Local Benefits	0.2938 (0.456)	0.3108 (0.463)	0.2517 (0.435)

Table 2: Parameter Estimates

Parameter	Model			
	Homogeneous Model	**Heterogeneous Model**	**Constrained Learning Model**	**Unconstrained Learning Model**
Price Coefficient $-\beta$	4.3403e-04 (5.4397e-07)	4.3877e-04 (6.0338e-07)	4.4134e-04 (6.1243e-07)	3.3412e-04 (7.1325e-06)
Variance of choice shock σ_{11}	0.6012 (0.0091)	0.2364 (0.0193)	0.2148 (0.1028)	0.2737 (0.0126)
Variance of usage shock σ_{22}	0.3980 (0.1873)	0.0737 (0.0344)	0.1342 (0.0502)	0.0109 (0.0058)
Covariance between these shocks σ_{12}	0.1763 (0.0912)	-0.0669 (0.0369)	-0.0739 (0.0428)	-0.0322 (0.0203)
Intercept - α	4.9016 (0.0373)	4.9102 (0.0924)	4.8931 (0.1142)	4.8527 (0.1179)
Household Size	0.1931 (0.0063)	0.0812 (0.0154)	0.0934 (0.0241)	0.0976 (0.0283)
Number of Teens in the household	0.2014 (0.0447)	-0.0217 (0.2398)	0.0531 (0.0296)	0.0410 (0.0306)
Head of the household is college educated	-0.0957 (0.0477)	-0.0712 (0.0349)	-0.0703 (0.0303)	-0.0758 (0.0265)
Received Federal/Local Benefits	0.2313 (0.0537)	0.0384 (0.0057)	0.0973 (0.0158)	0.1029 (0.0341)
Dummy for November	-0.3216 (0.0575)	-0.1060 (0.0136)	-0.1218 (0.0361)	-0.1327 (0.0473)
Dummy for December	-0.2353 (0.0786)	-0.0851 (0.0201)	-0.0947 (0.0380)	-0.1183 (0.0480)
Variance for heterogeneity on the intercept σ_{α}^{2}		0.6735 (0.0327)	0.7183 (0.0461)	0.6506 (0.0386)
Signal Variance for Measured Plan $\ln\left(\sigma_{sM}^{2}\right)$				-9.0865 (0.7098)
Signal Variance for Fixed Plan $\ln\left(\sigma_{sF}^{2}\right)$				8.5728 (0.5535)
Log Likelihood	10039.28	8936.47	8892.06	8148.94

Notes:
1. Standard errors are reported in parenthesis
2. Recollect that $\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix}$

Table 3: Price Elasticities

	Model			
	Homogeneous Model	**Heterogeneous Model**	**Constrained Learning Model**	**Unconstrained Learning Model**
Usage Elasticity for Measured Plan (% change in usage of measured plan across all measured plan consumers for every 1% increase in price)	-2.7453	-1.7582	-1.8311	-1.9241
Choice Elasticity for Measured Plan (% change in choice probability of measured plan for every 1% increase in price)	-1.8130	-1.0305	-1.0492	-1.0631

Table 4: Value of Information

Level of information	**Value of Information (average per consumer per month in $)**			
	Homogenous Model	**Heterogeneous Model**	**Constrained Learning Model**	**Unconstrained Learning Model**
Full Information (both ν_{it} and α_i)	0.1873	0.4610	0.4409	0.4498
Limited Information (only α_i)	-	-	0.3674	0.4447

Table 5: Revenue Impact of the Removal of One of the Plans*

Plan Removed	Expected Revenue	Increase of firm revenues
Neither (current scenario)	$85999.02	-
Measured Plan removed	$93143.93	$7144.91
Fixed Plan removed	$99174.28	$13175.26

*Computed using the estimates of the heterogeneous mode

Table 6: Consumer Surplus[a]
Compensating Variation (compared to the existing situation)

Plan Removed	Compensating Variation (total across consumers and across 3 months)
Measured Plan removed	$30843.16[b]
Fixed Plan removed	$126594.23[b]

[a] This simulation uses the estimates of the heterogeneous model
[b] The interpretation of these numbers is that consumers would have to be compensated by these amounts (in total across all consumers across all months) for the removal of the measured plan and fixed plan respectively.

Table 7: Firm Revenues for a New Plan While Keeping Consumer Surplus Unchanged (compared to the current plan)[a]

Scenario	Firm Revenues
Current Plan	$85999.02
New Plan with Measured Plan Tariff : Fee = $10.00, Price = 0.1062	$92138.90
Difference	$6139.88

[a] This simulation uses the estimates of the heterogeneous model

Table 8: Consumer Surplus for a New Plan While Keeping Firm Revenues Unchanged (compared to the current plan)[a]

Scenario	Compensating Variation
New Plan with Measured Plan Tariff : Fee = $16.00, Price = $0.0223	-21462.16[b]

[a] This simulation uses the estimates of the heterogeneous model
[b] A negative compensating variation suggests that consumers would be willing to pay this amount (in total, across all consumers and all months) to have the option of this new plan instead of the old plan – i.e. their consumer surplus is higher in the new scenario by this amount, compared to the existing scenario.

Figure 1: Consumer Decision Process – Base Model

Decision Stage	Plan Choice Shock η_{it}	Usage Shock ν_{it}	Type α_i
Plan Choice (beginning of the month)	Known to consumer	Unobserved by consumer, but its distribution known	Known to consumer
Usage Decision (during the month)	Known to consumer	Known to consumer	Known to consumer

(other parameters of the utility function observed at all stages)

Figure 2: Consumer Decision Process – Constrained Learning Model

Decision Stage	Plan Choice Shock η_{it}	Usage Shock ν_{it}	Type $\tilde{\alpha}_i$
Plan Choice (beginning of the month)	Known to consumer	Unobserved by consumer, but its distribution known	Known with uncertainty – consumer uses the most updated belief
Usage Decision (during the month)	Known to consumer	The sum of these two terms, i.e. the realization of $\left(\tilde{\alpha}_i + \nu_{it}\right)$ observed by the consumer	
Updation of belief (End of the month)	N.A.	Only measured plan consumers update their belief, using information on usage in their telephone bills	

(other parameters of the utility function observed at all stages)

Figure 3: Consumer Decision Process – Unconstrained Learning Model

Decision Stage	Plan Choice Shock η_{it}	Usage Shock ν_{it}	Type $\tilde{\alpha}_i$
Plan Choice (beginning of the month)	Known to consumer	Unobserved by consumer, but its distribution known	Known with uncertainty – consumer uses the most updated belief
Usage Decision (during the month)	Known to consumer	Known to consumer	Known with uncertainty – belief unchanged w.r.t. plan choice stage
Updation of belief (End of the month)	N.A.	N.A.	Consumer updates belief based on a noisy signal received from that month's usage

(other parameters of the utility function observed at all stages)