Appendices: Model Extensions

Appendix A: Forward-Looking Model with Option Value

Bayesian learning as characterized by the evolution of the posterior belief in Equations 7 and 8 implies that as a household accumulates more experience with the service, its belief about the quality would get more precise (i.e., $\sigma^2_{Qht} \to 0$). As a result, in addition to the contemporaneous expected utility from subscribing, the household would also derive an option value from continuing with the service. The option value arises because the household can gather more information about the service by subscribing and hence make a more informed decision in the next period (Hitsch (2006)). The total expected utility (including the option value) that the household would derive from subscribing can be written in the form of a Bellman equation as

$$\begin{aligned} W^1(\Omega_{ht}) &= \bar{V}_{1ht} + \epsilon_{1ht} + \delta \int E_\epsilon[\max\left\{W^1(\Omega_{ht+1}), W^0(\Omega_{ht+1})\right\}|\Omega_{ht}]d(\Omega_{ht+1}|\Omega_{ht}) \\ &= \bar{V}_{1ht} + \epsilon_{1ht} + \Delta_{1ht} \\ &= U_{1h}(\Omega_{ht}) + \epsilon_{1ht}, \end{aligned} \tag{A.1}$$

where, Ω_{ht} is the set of state variables (discussed in the estimation section) that influence household h's utility from the service at time t and δ is the discount factor. The term $\bar{V}_{1ht}$ in Equation A1 captures the per-period flow utility that the household expects to derive from subscribing to the service at time t. The terms $W^0_h(.)$ and $W^1_h(.)$ capture the total utility from terminating and subscribing to the service, respectively, as a function of the state variables and Δ_{1ht} reflects the option value from subscribing to the service with the expectation taken over the distribution of the unobserved component of the utility, ϵ_{1ht}. The integration in Equation (A1) is performed over the distribution of the state variables at time t+1 (Ω_{ht+1}) conditional on the observed values at time t (Ω_{ht}) and reflects the stochastic nature of their evolution. The term $U_{1h}(\Omega_{ht})$ is the total observed (by the researcher) component of the utility that household h derives from subscribing to the service given the state variables, Ω_{ht}.

The household will subscribe to the service in a given period if the total expected utility from subscribing (including the option value) during that period exceeds the corresponding expected utility from not subscribing. In the data, we do not observe households reactivating the service after terminating. Consequently, we treat stopping subscription as a terminal decision. Therefore, there is no option value if a household decides to terminate the service. Since we normalize the observed component of the flow utility from terminating the service is 0 (Equation 3), the observed component of the total utility from terminating the service, $U_{1h}(\Omega_{ht})$, is also 0. Therefore, the household would subscribe if

$$W^1(\Omega_{ht}) = U_{1h}(\Omega_{ht}) + \epsilon_{1ht} > \epsilon_{0ht}. \tag{A.2}$$

We assume that the household-specific idiosyncratic shocks, ϵ, follow a type I extreme value distribution. Given the above distributional assumption and the normalization of the utility from terminating the service, Equation A1 can be rewritten as

$$\begin{aligned} W^1(\Omega_{ht}) &= \bar{V}_{1ht} + \epsilon_{1ht} + \delta \int \ln\left\{1 + \exp\left(U_{1h}(\Omega_{ht+1})\right)\right\} |\Omega_{ht}] d(\Omega_{ht+1}|\Omega_{ht}) \\ &= U_{1h}(\Omega_{ht}) + \epsilon_{1ht}. \end{aligned} \tag{A.3}$$

Implications for the Option Value

Option value is typically an increasing function of the per-period flow utility. The extent to which flow utility is an increasing or decreasing function of variability is determined by the tradeoff between the adverse effect via risk aversion and the positive effect of deterring learning, at least for some households. The other driver of option value is the extent to which staying with the service helps the household to make a more informed decision in the future. If the household already has precise knowledge about the average quality it experiences, this benefit is likely to be small. Consequently, households that start with higher uncertainty about the average quality of the service and see larger gains in precision as they accumulate more information are likely to benefit more by staying longer with the service. Thus, one can conjecture that for a given flow utility, high variability is likely to induce customers to stay longer with the service.

Estimation

Given our model specification, there are four sets of state variables: (a) the mean belief about the quality of the service at any period, $\bar{Q}_{ht}$, (b) uncertainty about this belief σ^2_{Qht}, (c) seasonality, and (d) demographic characteristics that act as shifters of the intrinsic preference for the service. Of these, the demographic characteristics are not dynamic but require us to compute the value function for each combination of values that they can take. In order to reduce the computational burden, we dichotomize the five demographic variables based on a median split. Therefore, our estimation involves computing 32 value functions corresponding to all possible combinations of demographic variables. As noted in Equation 1, the seasonality variable captures shifts in the intrinsic propensity to subscribe to the service during different months of the year. Consequently, while this state variable is intrinsically dynamic, its evolution is deterministic.

As in any learning model with option value, the two key state variables in our context are the mean and uncertainty about the unknown entity, the quality of the service. Equation 7 governs the law of motion for the belief about mean quality, $\bar{Q}_{ht}$. Given the distributional assumptions of normal prior and signals, as in Hitsch (2006), we can characterize the transition density of $\bar{Q}_{ht}|\bar{Q}_{ht-1}$ as $N\left(\bar{Q}_{ht-1}, \frac{\sigma^4_{Qht-1}}{\sigma^2_{Qht-1}+\sigma^2_h}\right)$. Equation 8 characterizes the evolution of the uncertainty about the average quality of the service. Unlike the mean, the uncertainty evolves in a deterministic manner as a function of the signal variance, σ^2_h. Furthermore, as discussed elsewhere, this uncertainty always declines as a household accumulates more information.

We recast the consumer's decision as a finite horizon problem when we compute the value functions. Specifically, we set T=30 as the terminal period and compute the value functions via backward induction.[1] Together, we have two deterministic state variables (demographic characteristics and seasonality) and two continuous ones. To accommodate the continuous state variables, we evaluate the value functions on a discrete grid of 20 points defined by Chebyshev zeros (Judd (1998)). We used Gaussian quadrature to evaluate the integral in Equation 7. Note that the integration requires us to evaluate the value function outside the set of grid points. To this end, we approximate the value function using a Chebyshev tensor polynomial of degree 4. Similarly, we use Chebyshev interpolation to translate the value functions evaluated at grid points to the actual values of the state variables for individual households over time. We use a discount factor of 0.99 in our estimation.

Results

We present the results from this estimation in Tables A1-A2. The forward-looking model fits the data slightly better than the myopic version (log-likelihood = -2995.162 vs. -3008.51 for the myopic version). The composition of the two segments are similar to those in the myopic version, albeit with some minor differences. In Figure A1, we present the predicted termination probabilities implied by the forward-looking model. As in the case of the myopic model the forward-looking version can replicate the interaction effect that we observe in the data. In Table A3, we present the effect of a 1% increase in signal quality on termination probability. Once again, the results suggest that households that experience high variability are less responsive to improvements in signal quality, both in absolute and percentage terms. Overall, the results from the forward-looking model are consistent with those from the myopic version presented in the paper.

Appendix B: Accounting for the Bounded Nature of Signals

Since the observed signal quality is bounded between 0 and 2.4, we need to account for this censoring. While choosing reasonable approach to account for the bounded nature of quality, we considered two criteria. First, since learning models with non-conjugate distributions are hard to tackle, we wanted to stay within the realm of conjugate distributions. Second, we wanted to ensure that the model reflected the model-free evidence in the data that households that experience high variability in quality learn at a slower rate. This criterion eliminated some natural conjugate distributions that naturally accommodate bounded data, such as beta-binomial.

We account for the bounded nature of signal quality by defining an underlying latent signal quality that is unbounded and can thus be treated as normal. Staying within the normal family preserves conjugacy and thus renders the problem computationally tractable. Households learn about this latent quality through their experience. Thus, households have latent perceptions about the realized signal quality, Q^*_{ht}, that is unbounded, which in corresponds to the realized bounded signal quality, Q_{ht} in Equations 1 and 2. We assume that Q_{ht} is a monotonic transformation of Q^*_{ht} such that

$$Q_{ht} = \begin{array}{c} Q^*_{ht} \;\; if \; 0 < Q^*_{ht} < 2.4 \\ 0 \;\; if \; Q^*_{ht} \leq 0 \\ 2.4 \;\; if \; Q^*_{ht} \geq 2.4 \end{array} . \quad \text{(B.1)}$$

[1] Recall that our data span 13 periods.

Our rationale for choosing this approach is as follows. Although the latent service quality, as perceived by the customer, might be unbounded, in most common applications, managers typically measure them in a discrete, bounded scale (e.g., a seven point scale as in SERVQUAL). The common interpretation is that each discrete rating point corresponds to the latent quality falling within a certain range of values. For example, if Q^* is the latent quality in unbounded space and Q is the measured quality in a K-point scale, it is common to express the relationship between Q and Q^* as

$$\begin{gathered} Q = 1 \; if \; Q^* < \zeta^1 \\ Q = K, \; K = 2, \; 3, \; ..., \; K-1, \; if \; \zeta^{K-1} \leq Q^* < \zeta^K, \\ Q = K \; if \; Q^* \geq \zeta^1 \end{gathered} \tag{B.2}$$

where, ζ^K, $K = 1, \; 2, \; 3, \; ..., \; K$, are the thresholds in the latent service quality space.

In our formulation, we assume that at time t, the uncertainty about the household's true latent quality is distributed $N\left(\bar{Q}^*_{ht}, \sigma^2_{Q^*ht}\right)$ and the corresponding mean of the realized signal is $\bar{Q}_{ht}$, while the variance is σ^2_{Qht}. Given the censored normal formulation, we can derive closed form expressions for the moments of the realized signal quality. In similar vein, we assume that the temporal uncertainty is distributed $N\left(0, \sigma^2_{*h}\right)$. Therefore, the total uncertainty perceived by the household about the quality of the service in the latent space at time t is the sum of the household's perceived uncertainty about the average quality of the service it receives ($\sigma^2_{Q^*ht}$) and the temporal variation it experiences (σ^2_{*h}), i.e., $\sigma^{*2}_{ht} = \sigma^2_{Q^*ht} + \sigma^2_{*h}$. Over time, the household accumulates experience with the service and updates its beliefs accordingly in the latent quality space, which in turn would lead to updating of beliefs in the realized quality space. We assume that households are Bayesian learners. Consequently, the mean converges to the true average latent quality received by the household, i.e., Q^*_h and the corresponding uncertainty ($\sigma^2_{Q^*ht}$) converges to 0.

We use two different empirical specifications. In the first specification, we assume that what matters to their subscription decision is the corresponding signal quality that is bounded between 0 and 2.4. One can impose these bounds by treating the realized signal as a censored outcome of the underlying latent variable. The approach would require us to transform the latent posterior belief into the corresponding expected quality and variance that would eventually affect the subscription decision.

The expression for the expected utility in Equation 2 is

$$\bar{V}_{1ht} = E[\tilde{V}_{1ht}] = \alpha_h + \beta_h \bar{Q}_{ht} - \gamma \bar{Q}^2{}_{ht} - \gamma \sigma^2_{ht} + \psi D_h + \tau S_t + \epsilon_{1ht}. \tag{B.3}$$

In the above equation, $\bar{Q}_{ht}$ is the mean expected quality in the bounded space (i.e., in terms of the number of new movies downloaded) and σ^2_{ht} is the corresponding total variability as perceived by the household at time t. The expressions for $\bar{Q}_{ht}$ and σ^2_{ht} follow from the properties of the censored normal distribution such that

$$\bar{Q}_{ht} = (\Phi_2 - \Phi_1)\left\{\bar{Q}^*_{ht} + \frac{\phi_1-\phi_2}{\Phi_2-\Phi_1}\sigma^*_{ht}\right\} + 2.4\,(1-\Phi_2)$$

$$\sigma^2_{ht} = \begin{array}{c}\left[(\Phi_2-\Phi_1)\left\{1+\frac{\frac{-\bar{Q}^*_{ht}}{\sigma^*_{ht}}\phi_1-\frac{2.4-\bar{Q}^*_{ht}}{\sigma^*_{ht}}\phi_2}{\Phi_2-\Phi_1}-\left(\frac{\phi_1-\phi_2}{\Phi_2-\Phi_1}\right)^2\right\}\sigma^{*2}_{ht}\right] \\ +\left[\Phi_1\left(-\bar{Q}^*_{ht}\right)^2+(1-\Phi_2)\left(2.4-\bar{Q}^*_{ht}\right)^2+(\Phi_2-\Phi_1)\left\{\bar{Q}_{ht}-\left(\bar{Q}^*_{ht}+\frac{\phi_1-\phi_2}{\Phi_2-\Phi_1}\sigma^*_{ht}\right)\right\}^2\right]\end{array}. \quad \text{(B.4)}$$

In the above expressions, $\bar{Q}^*_{ht}$ is the expected value of signal quality in the latent space, while $\sigma^{*2}_{ht} = \sigma^2_{Q^*ht} + \sigma^2_{*h}$ is the total uncertainty as perceived by household h at time t. he terms Φ_1 and Φ_2 correspond to the CDF of the standard normal distribution evaluated at $\frac{-\bar{Q}^*_{ht}}{\sigma^*_{ht}}$ and $\frac{2.4-\bar{Q}^*_{ht}}{\sigma^*_{ht}}$, respectively. Note that these two points correspond to the normalized lower and upper censoring limits, i.e., 0 and 2.4, respectively. The terms ϕ_1 and ϕ_2 are the corresponding standard normal density functions. The expression of the variance of the bounded signal quality, σ^2_{ht} in Equation 6 is derived as the sum of the expected value of the variance (the term within the first square brackets) and the variance of the conditional mean (the term within the second square brackets).

In the second approach, we assume that the household's utility is a function of the latent quality, not the observed, bounded values. Under this assumption, we can write the expected utility in Equation 2 as

$$\bar{V}_{1ht} = E[\tilde{V}_{1ht}] = \alpha_h + \beta_h\bar{Q}^*_{ht} - \gamma\left(\bar{Q}^*_{ht}\right)^2 - \gamma\sigma^{*2}_{ht} + \psi D_h + \tau S_t + \epsilon_{1ht}. \quad \text{(B.5)}$$

Further, we relax the assumption that within the bounded space, the latent quality is the same as the measured quality.

$$Q_{ht} = \begin{array}{c} Q^{**}_{ht}\ \ if\ a < Q^{**}_{ht} < a + 2.4b \\ 0\ \ if\ Q^{**}_{ht} \le a \\ 2.4\ \ if\ Q^{**}_{ht} \ge a + 2.4b \end{array} \quad \text{(B.6)}$$

In essense, the above formulation implies that the latent quality, Q^*_{ht} and Q^{**}_{ht} in Equations B1 and B6 have the following relationship.

$$Q^{**}_{ht} = a + bQ^*_{ht}. \quad \text{(B.7)}$$

Therefore, the first formulation imposes the restriction that signal translation parameter, $a = 0$ and the signal scale parameter, $b = 1$. Under the second formulation, we need to require the additional step of computing the mean and the variance of the quality in the bounded space. However, we need to estimate the signal translation parameter, a, and the signal scale parameter, b.

As in the literature, we assume that households update their beliefs about the true quality in the latent space of the service in a Bayesian manner. Each household has some prior belief about the latent quality of the service at the time of activation. We assume that this prior belief follows a normal distribution such that $\tilde{Q}^*_{h0} \sim N(Q^*_0, \sigma^2_{Q^*h0})$. During each period t, household h notes the quality of the service it receives (via the number of new movies in its set-top box) and updates its belief accordingly. As is common in the literature (see, for example Coscelli and Shum (2004)), we assume that the quality of the latent signals that the household receives each period comes from a normal distribution with variance σ^{*2}_h.

Since the model-free evidence suggests that the rate at which a household updates its belief about the quality of the service is inversely related to the variance of the signals it receives, we assume that households know the variability of the latent signals (i.e., σ^{*2}_h) that they receive. We compute σ_h^{*2} based on the observed mean and variance in the realized quality in the bounded space. We verify that data patterns such as differential learning and the interaction effect (which we had demonstrated based on the variability in the bounded space) exist when we consider the variability in the latent signals.

Given the conjugacy of the prior and signal, the posterior mean belief about the signal quality after t periods of subscribing (i.e., the prior at the beginning of period t +1) based on the information it has accumulated till time t can be written as

$$\bar{Q}^*_{ht} = \bar{Q}^*_{ht-1} + \frac{\sigma^2_{Q^*ht}}{\sigma^2_{Q^*ht} + \sigma{*}^2_h}[Q^*_{ht} - \bar{Q}^*_{ht-1}], \tag{B.8}$$

where, Q^*_{ht} is the actual signal quality in the latent space experienced by the household during period t and the posterior variance at the end of the period t (i.e., prior variance in period t+1) is

$$\sigma^2_{Q^*ht} = \frac{1}{\frac{1}{\sigma^2_{Q^*ht-1}} + \frac{1}{\sigma{*}^2_h}} = \frac{1}{\frac{1}{\sigma^2_0} + \frac{\tau_{ht}}{\sigma^2_{*h}}}. \tag{B.9}$$

In the above expression, τ_{ht} is the number of periods that household h has been with the service as of period t. Since households join the service at different time periods, the number of periods that household h is with the service (τ_h) would not correspond to the number of periods that the service has been active (t). In order to update the mean quality belief in the latent space as in Equation 7, we need to translate the realized signal quality in the 0-2.4 range, Q_{ht} into the corresponding value in the latent space. Given our assumption of a censored normal distribution for the underlying latent variable, when the realized signal quality is in the interior of the (0, 2.4) range, the latent quality would be the same as the realized quality. On the other hand, when the realized signal quality is 0 (2.4), we know that the underlying latent quality is less than 0 (greater than 2.4). Consequently, when the realized signal quality is either 0 or 2.4, we need to integrate Equation 7 over the corresponding range based on the prior distribution, i.e., $N\left(\bar{Q}^*_{ht}, \sigma^2_{Q^*ht}\right)$.

In the second approach, we assume that the household's utility is a function of the latent quality, not the observed, bounded values. Under this assumption, we can write the expected utility in Equation 2 as

$$\bar{V}_{1ht} = E[\tilde{V}_{1ht}] = \alpha_h + \beta_h \bar{Q}^*_{ht} - \gamma\left(\bar{Q}^*_{ht}\right)^2 - \gamma\sigma^{*2}_{ht} + \psi D_h + \tau S_t + \epsilon_{1ht}. \tag{B.10}$$

Further, we relax the assumption that within the bounded space, the latent quality is the same as the measured quality.

$$Q_{ht} = \begin{matrix} Q^{**}_{ht} \;\; if \;\; a < Q^{**}_{ht} < a + 2.4b \\ 0 \;\; if \;\; Q^{**}_{ht} \leq a \\ 2.4 \;\; if \;\; Q^{**}_{ht} \geq a + 2.4b \end{matrix} . \tag{B.11}$$

In essense, the above formulation implies that the latent quality, Q^*_{ht} and Q^{**}_{ht} in Equations B1 and B11 have the following relationship:

$$Q^{**}_{ht} = a + bQ^*_{ht}. \tag{B.12}$$

Therefore, the first formulation imposes the restriction that signal translation parameter, $a = 0$ and the signal scale parameter, $b = 1$. Under the second formulation, we need to require the additional step of computing the mean and the variance of the quality in the bounded space. However, we need to estimate the signal translation parameter, a , and the signal scale parameter, b .

Estimation Algorithm

Step 1: In period 0, we need prior beliefs in the latent space, Q_0^* and $\sigma^2_{Q^*h0}$. In the current set up, Q_0 in the bounded space is set to 2.4, while we estimate $\sigma^2_{Q^*h0}$ as a parameter. We need to translate Q_0 to the corresponding value in the latent space, Q_0^*. Alternatively, if we estimate Q_0^*as a parameter directly in the latent space, we don't need to translate it back to the bounded space.
Step 2: The household also knows the variability in the realized signal quality, σ_h^2. We need to convert this to the latent space, σ_h^{*2}. This translation would depend on the mean of the underlying distribution. We can evaluate this in the first period based on the prior mean, Q_0.
Step 3: In period t, household receives signal, Q_{ht} in the 0-2.4 range. Convert this to the corresponding quality in the latent space, Q_{ht}^*. We can then use these values in the latent space to compute the updated quality beliefs based on Equation 7. Specifically, we use the following logic:

$$\begin{array}{c} if\ \ 0 < Q_{ht} < 2.4,\ \ then\ Q_{ht}^* = Q_{ht} \\ if\ \ Q_{ht} = 0,\ \ then\ Q_{ht}^* < 0 \\ if\ \ Q_{ht} = 2.4,\ \ then\ Q_{ht}^* > 2.4 \end{array} .$$

Therefore, for the realized signal values that lie in the range $0 < Q_{ht} < 2.4$, we can treat the latent quality as the same as the realized quality.[2] For the realized values at the points of censoring, we need to integrate Equation 7 over the distribution of the censored normal. We can accomplish this by making draws from the truncated normal distribution and evaluating Equation 7 for each draw and taking the mean over the draws. We can use Equation 8 to compute the posterior beliefs.

Step 4: We now need to translate the mean and the variance to the corresponding values in the bounded space in order to compute the expected value. We can do this numerically in the logit case. In case of censored normal, we have closed form expressions for this translation.

Results

We present the estimates from this model in Table B1 and B2. The models that accounts for the bounded nature of signals fits the data worse than the version that doesn't (log-likelihood of -3016.18 and -3010.46 vs. -3008.51). Nevertheless, the results are fairly consistent across both versions of the model. As seen in Figure B1 and B2, the model that accounts for bouned signals can replicate the data patterns found in the data. Moreover, the effects of the 1% increase in termination probabilities reported in Table B3 are consistent with those in the main model presented in the paper.

[2]In the second specification we use the linear transformation of the realized signals to arrive at the latent signals.

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Table A1: Estimates from the Forward-Looking Model

PARAMETER	ESTIMATE	STD ERROR
INTERCEPT (SEGMENT 1)	0.618	0.129
INTERCEPT (SEGMENT 2)	-1.169	0.230
SIGNAL QUALITY EFFECT (SEGMENT 1)	0.442	0.057
SIGNAL QUALITY EFFECT (SEGMENT 2)	1.333	0.119
RISK AVERSION (EXP(.))	-1.518	0.085
OCTOBER	-1.605	0.339
NOVEMBER	1.103	0.107
DECEMBER	-0.353	0.173
JANUARY	-0.557	0.160
FEBRUARY	0.087	0.177
MARCH	-0.226	0.133
APRIL	-0.101	0.129
MAY	-0.084	0.165
JUNE	-0.235	0.153
JULY	-0.540	0.140
AUGUST	-0.215	0.180
SALT LAKE CITY	0.057	0.017
SPOKANE	0.076	0.024
INCOME	0.058	0.015
CHILD	-0.001	0.016
% OLD	0.005	0.016
SIGNAL QUALITY PRIOR VARIANCE (SEGMENT 1) (EXP(.))	-2.416	0.067
SIGNAL QUALITY PRIOR VARIANCE (SEGMENT 2) (EXP(.))	-2.451	0.227
TRANSFORMED PRIOR MEAN (SEGMENT 1)	-0.244	0.109
TRANSFORMED PRIOR MEAN (SEGMENT 2)	10.293	0.018
SEGMENT 1 MEMBERSHIP PARAMETER (INTERCEPT)	0.994	0.055
SEGMENT 1 MEMBERSHIP PARAMETER (EFFECT OF INTRINSIC PROPENSITY TO USE THE SERVICE)	-0.210	0.033
LL	-2995.162	

Table A2: Segment Characteristics for the Forward-Looking Model

	SEGMENT 1	SEGMENT 2
SEGMENT SIZE	2312	934
SIGNAL QUALITY PRIOR MEAN (ESTIMATED)	1.055	2.4
SIGNAL QUALITY PRIOR VARIANCE (ESTIMATED)	0.083	0.087
MEAN MONTHLY RENTAL (USAGE)	2.759	4.574
AVG. SIGNAL QUALITY	1.460	1.286
% TERMINATING	4%	65%

Table A3: Effect of a 1% increase in Signal Quality on Termination Rates (Forward-Looking Model)

	Absolute Change in Termination Rate		% Change in Termination Rate (Elasticity)	
Signal Quality	Low-Variability Households	High-Variability Households	Low-Variability Households	High-Variability Households
0-0.5	-0.13%	-0.06%	-0.31%	-0.14%
0.5-1	-0.16%	-0.09%	-0.29%	-0.27%
1-1.5	-0.26%	-0.13%	-1.08%	-0.47%
1.5-2	-0.21%	-0.12%	-1.55%	-0.60%
> 2	-0.22%	-0.05%	-2.06%	-0.29%
Average	**-0.21%**	**-0.11%**	**-1.42%**	**-0.43%**

Figure A1: Termination Rates Implied by the Model with Option Value

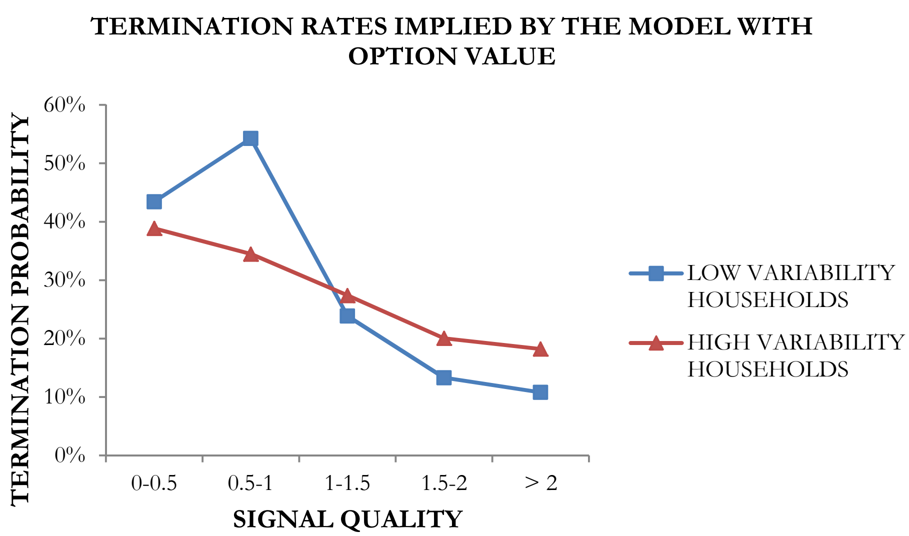

Table B1: Estimates from the Model with Bounded Signals

	UTILITY AS A FUNCTION OF BOUNDED QUALITY		UTILITY AS A FUNCTION OF LATENT QUALITY	
PARAMETER	ESTIMATE	STD.ERROR	ESTIMATE	STD.ERROR
INTERCEPT (SEGMENT 1)	-4.26	0.03	-7.06	0.45
INTERCEPT (SEGMENT 2)	4.34	0.26	3.65	0.04
SIGNAL QUALITY EFFECT (SEGMENT 1)	6.59	0.06	5.28	0.21
SIGNAL QUALITY EFFECT (SEGMENT 2)	0.71	0.25	0.82	0.49
RISK AVERSION (EXP(.))	0.10	0.03	-1.89	0.06
OCTOBER	-0.27	0.15	-0.27	0.03
NOVEMBER	1.02	0.55	1.08	0.11
DECEMBER	-0.10	0.28	-0.06	0.01
JANUARY	0.01	0.13	0.02	0.00
FEBRUARY	0.46	0.24	0.47	0.05
MARCH	0.19	0.07	0.23	0.02
APRIL	0.19	0.07	0.23	0.02
MAY	0.02	0.01	0.04	0.00
JUNE	-0.19	0.08	-0.18	0.02
JULY	-0.26	0.14	-0.25	0.03
AUGUST	0.03	0.01	0.03	0.00
SALT LAKE CITY	0.44	0.15	0.43	0.04
SPOKANE	0.56	0.30	0.57	0.06
INCOME	0.38	0.14	0.39	0.04
CHILD	0.05	0.02	0.04	0.00
% OLD	0.05	0.02	0.02	0.00
SIGNAL QUALITY PRIOR VARIANCE (SEGMENT 1) (EXP(.))	-0.14	0.08	-1.11	0.01
SIGNAL QUALITY PRIOR VARIANCE (SEGMENT 2) (EXP(.))	-1.79	0.01	-2.28	0.02
PRIOR MEAN (SEGMENT 1)	3.00	0.59	13.57	1.00
PRIOR MEAN (SEGMENT 2)	-1.09	0.35	1.04	0.00
SEGMENT 1 MEMBERSHIP PARAMETER (INTERCEPT)	-1.35	0.01	-1.67	0.08
SEGMENT 1 MEMBERSHIP PARAMETER (EFFECT OF INTRINSIC PROPENSITY TO USE THE SERVICE)	0.24	0.00	0.23	0.01
LATENT SIGNAL TRANSLATION PARAMETER (A)			0.64	0.05
LATENT SIGNAL SCALE PARAMETER (B)			0.93	0.04
LL	-3016.18		-3010.46	

Table B2: Segment Characteristics (Model with Bounded Signals)

	UTILITY AS A FUNCTION OF BOUNDED QUALITY		UTILITY AS A FUNCTION OF LATENT QUALITY	
	SEGMENT 1	SEGMENT 2	SEGMENT 1	SEGMENT 2
SEGMENT SIZE	767	2479	437	2809
LATENT SIGNAL QUALITY PRIOR MEAN (ESTIMATED)	2.997	-1.094	3.000	1.429
SIGNAL QUALITY PRIOR VARIANCE	0.086	0.090	0.329	0.102
MEAN MONTHLY RENTAL (USAGE)	4.578	2.880	5.049	3.006
AVG. TIME TO ADOPTION	4.937	4.620	4.654	4.701
AVG. LENGTTH OF ACTIVITY	6.160	9.182	6.986	8.698
AVG. SIGNAL QUALITY	1.21	1.470	1.091	1.459
% TERMINATING	69%	7%	65%	15%
VARIANCE IN SIGNAL QUALITY	0.487	0.435	0.386	0.457

Table B3: Effect of a 1% increase in Signal Quality on Termination Rates (Models that Account for Bounded Signals)

	Utility as a Function of Bounded Signals				Utility as a Function of Latent Signals			
	Absolute Change in Termination Rate		% Change in Termination Rate (Elasticity)		Absolute Change in Termination Rate		% Change in Termination Rate (Elasticity)	
Signal Quality	Low-Variability Households	High-Variability Households	Low-Variability Households	High-Variability Households	Low-Variability Households	High-Variability Households	Low-Variability Households	High-Variability Households
0-0.5	-0.03%	-0.02%	-0.07%	-0.05%	-0.04%	-0.05%	-0.09%	-0.10%
0.5-1	-0.18%	-0.07%	-0.35%	-0.20%	-0.23%	-0.11%	-0.49%	-0.26%
1-1.5	-0.22%	-0.14%	-0.99%	-0.59%	-0.40%	-0.25%	-1.33%	-0.83%
1.5-2	-0.18%	-0.13%	-1.22%	-0.58%	-0.26%	-0.22%	-1.45%	-0.98%
> 2	-0.18%	-0.14%	-1.29%	-0.57%	-0.11%	-0.10%	-0.95%	-0.44%
Average	**-0.17%**	**-0.11%**	**-1.03%**	**-0.45%**	**-0.21%**	**-0.19%**	**-1.07%**	**-0.68%**

Figure B1: Termination Rates Implied by the Model that Accounts for Bounded Signals (Utility as a Function of Bounded Signals)

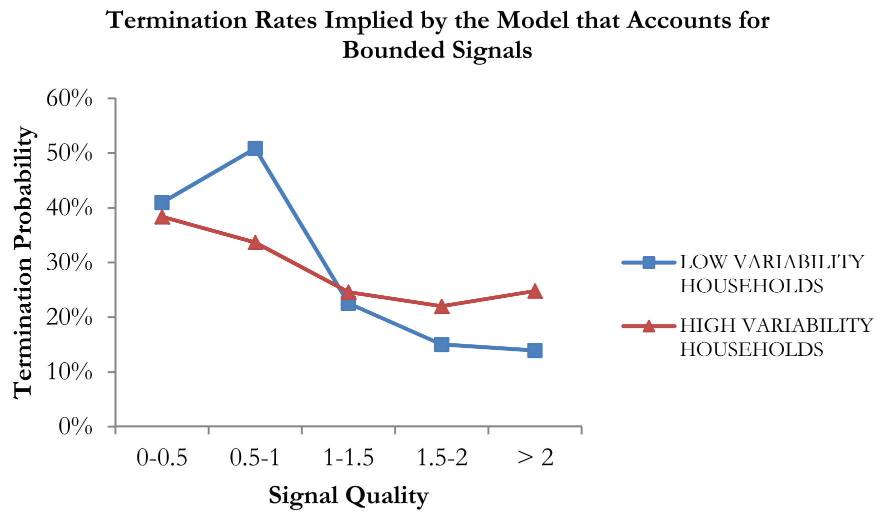

Figure B2: Termination Rates Implied by the Model that Accounts for Bounded Signals (Utility as a Function of Latent Signals)