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Service Quality Variability and Termination Behavior

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We investigate the roles of the level and variability in quality in driving customer retention for a new service. We present model-free evidence that whereas high average quality helps in retaining customers, high variability leads to higher termination rates. Apart from these main effects, we use model-free evidence to document the presence of (a) an interaction effect between average service quality and its variability on termination rates, (b) customer learning about service quality over time, and (c) a slower rate of learning among households that experience high variability. We postulate a mechanism involving risk aversion and learning, which can induce this interaction effect, and test this against several alternative explanations. We show that it is important to consider variability in quality while inferring the impact of improvements to average quality—ignoring the interaction effect between average quality and variability leads to an 18%–64% (5%–31%) overestimation (underestimation) of quality improvement elasticities among high-variability (low-variability) households. Given that responsiveness to quality decreases with variability, it is better for the firm to focus quality improvement efforts on customers experiencing low variability; increasing average quality by 1% lowers termination by 1.1% for low-variability households, but only by 0.41% for high-variability households.

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1. Introduction

When customers of a service experience low levels of quality, on average, they are more likely to terminate the service compared to those experiencing higher average quality. This can be due to a variety of reasons, including disillusionment and/or inability to use the service (e.g., cell phone usage for a traveling sales person depends on the quality of the service in the places traveled). The importance of maintaining a high level of service quality in order to increase customer retention is echoed in the academic marketing literature (see, e.g., Bolton et al. 2006). Managerially, the quality elasticity metric—i.e., how retention changes due to a change in the average quality—is an important input into the actual decision to change the average quality being offered to customers.

Researchers in marketing have also investigated the effects of service quality variability on customer retention (see Kannan and Proenca 2010 for a review of this literature). Unlike the recommendation about the average service quality, the effect of variability on consumer retention has been viewed more ambiguously in the literature. The dominant view is that customers are likely to penalize a service for high variability, possibly because of "risk" or variability aversion, resulting in lower adoption (Meyer 1981) and retention (Rust et al. 1999). On the other hand, researchers have also argued that variability can increase retention if it induces a significant number of positive customer experiences (e.g., Bolton et al. 2006). Although the literature suggests that managers need to account for quality variability when assessing a customer's retention, accounting for or ignoring variability may also have implications for a manager's assessment of quality elasticity. This empirical relationship between quality variability and quality elasticity has received limited attention in the empirical literature.

In this paper, we investigate the roles of the mean and variability in service quality in driving *customer retention* in the context of a new video on demand (VOD) service. Our analysis of the role of average quality and variability in customer retention proceeds as follows. We begin by providing model-free evidence that consumers who are subject to more variability are more likely to terminate the service and that the effect of mean quality on customer retention depends on the variability of the service and vice versa. Further, we establish that the interaction between mean quality and its variability is not an artifact of the bounded nature of observed quality that is common in many empirical contexts, including ours. Since the customers in our data set are new to the service, they also likely to face uncertainty regarding the quality of service they receive (e.g., Mehta et al. 2004, Narayanan et al. 2005). Our examination of data provides *prima facie* evidence that customers try to resolve this uncertainty by learning about the quality of the service they receive. Furthermore, these patterns indicate that the extent of learning is a decreasing function of the variability that the customer experiences.

Next, we postulate a mechanism involving risk aversion (based on the observation of higher variability leading to higher termination rates) and learning (since the service is new) that can rationalize these data patterns. This proposed mechanism works as follows. First, since we observe that customers dislike variability on average, we take this as evidence of customers' risk aversion. Second, we observe customers' learning over time with higher variability deterring learning about the true quality. As a result, customers experiencing high variability are less likely to update their beliefs about the true quality of the service. As an extreme outcome, households that have a higher prior belief about the quality of the service vis-à-vis what they actually experience are less likely to terminate in the presence of high variability. Thus, the key trade-off is the following: high variability reduces the expected utility via risk aversion and thereby encourages termination. On the other hand, high variability can deter learning about the true quality of the service. This, in turn, can lead to higher retention among customers with high prior quality beliefs who receive low quality. Therefore, such a trade-off can explain the interaction effect observed in the data even when observed quality is not bounded.[1] The trade-off between risk aversion and learning deterrence is also alluded to in the experimental psychology literature (e.g., Pleskac 2008).

The mechanism for the interaction effect that we propose is similar in spirit to Sun (2012), albeit with some notable differences. In her paper, Sun (2012) argues that at the higher end of the average quality spectrum, high variability can lower adoption, possibly because of risk aversion. But at lower average levels, high variability can lead to higher adoption when customers are informed that it is a niche product/service. Meyer (1981) demonstrates such an interaction effect between average quality and variability; i.e., purchase intent increases more steeply with mean quality when variability is low. Since retention deals with consumers' own experiences of service quality postadoption rather than the information contained in others' experiences prior to adoption, the "niche appeal" argument advanced by Sun (2012) for the interaction effect does not apply in our case.

We then estimate the model that incorporates risk aversion and learning and demonstrate the differential effects of variability on customer retention. Our characterization of the model-free evidence and estimation exploits exogeneity of the cross-sectional differences in the average quality across households and of the temporal quality variation within a household (see Nam et al. 2010 for a discussion). As we observe the quality experienced by each household over time and can hence compute household-specific variability, we are able to identify the effects of risk aversion. Further, we estimate the parameters of our model under the assumption that households resolve the uncertainty of the quality in service that they receive via a Bayesian learning process. We compare our specification to those that provide alternative explanations for the data patterns and show that our proposed account fits the data better than those models.

We derive several managerially relevant implications from our data and analysis. First, we show that it is important to consider variability in quality while inferring the impact of improvements to average quality; not considering variability is likely to result in inaccurate inferences regarding the effect of quality improvements. Our results show that ignoring the interaction effect between average quality and variability leads to an 18%–64% (5%–31%) overestimation (underestimation) of quality improvement elasticities among high-variability (low-variability) households. Second, given that responsiveness to quality decreases with variability, it is better for a firm to focus quality improvement efforts on customers experiencing low variability; increasing average quality by 1% lowers termination by 1.1% for low-variability households, but only by 0.41% for high-variability households. Third, consistent with the large body of research in the services marketing literature, our results show that for long-standing (i.e., not new) customers, a high level of average quality and a low level of variance drive increased retention. However, the implications are nuanced for new customers. In the presence of risk/variability averse consumers, a manager can either decrease variability or increase the mean quality. Our results suggest that at intermediate quality levels, increasing the mean by one unit (movie) is as effective as lowering the standard deviation by one unit (movie). In contrast, at high quality levels, we need a much larger increase in the mean number of movies (2.25) to achieve the same lower termination as we get by lowering standard deviation by one movie. Therefore, at low quality levels, it is better to increase the mean, whereas it is better to

[1] We show this via simulation.

decrease the variability at high quality levels. Our results have implications for how firms (in industries beyond the VOD business under consideration) with limited resources might choose to allocate them. An example of this is the cellular phone service industry, where firms face trade-offs between offering reliable service (more towers for coverage) and improving average quality by adopting new technologies (such as 4G LTE).[2]

We also provide several extensions and robustness checks for our model and estimation results. First, the presence of learning may lead to households making intertemporal trade-offs, i.e., being willing to continue with the service to learn about its quality (see, e.g., Erdem and Keane 1996, Hitsch 2006). We provide an extension of our model to account for such forward-looking behavior of households. Second, although the Bayesian model we specify for household learning assumes that the true quality and the quality "signals" for households come from a normal distribution, the signal quality data are bounded. We therefore modify the learning model to account for this feature of the data to assess the sensitivity of our results. Third, we discuss an extension of our model that allows for household uncertainty regarding the variance of signal quality. In addition to these model extensions, we investigate several alternate model specifications. In particular, we look at a model that allows for the effects of extreme positive and negative signals received and one that incorporates the effects of the "gain" and "loss" associated with the most recent signal received by the household.

The rest of this paper is organized as follows. We first discuss the data used in our analysis and describe some key patterns. We then present the model, discuss its implications, and review the estimation approach. Next, we present our empirical results. We then provide results from model extensions and alternative specifications. Finally, we provide some concluding comments.

2. Data

The data used in this study come from a VOD service that was test marketed for over a year in three U.S. cities: Jacksonville, FL; Salt Lake City, UT; and Spokane, WA. Our data span the first 13 months of this test market from October 2003 to October 2004.[3] The service allowed subscribing households to rent movies from a database of 100 titles that reside in a set-top box with a built-in antenna. During each month, the movie database was to be updated by up to a maximum of 40 new titles via a terrestrial signal from a local broadcasting tower to the set-top box. The one-time activation fee was \$29.99, the monthly subscription fee for the service was \$7.99, and the average per-movie-rental fee was \$1.99. Not paying the subscription fee in a given month resulted in termination of the service. Reactivating required repayment of the activation fee. The data contain household level information on subscription and termination each month. The data used in our analysis consists of 3,246 households that adopted the service, of which 695 (i.e., 21.4%) terminated it during the period of our analysis. None of the terminating households readopted the service. Of the households in our sample, 44.1% were from Salt Lake City, 43.3% were from Jacksonville, and the remaining 12.6% were from Spokane.[4]

A unique characteristic of the service is that although 40 movies can potentially be updated in its database every month, the actual outcome (the number of movies updated) depends on the signal quality that the household receives during that period.[5] The movies are updated on a weekly basis, with 10 being the maximum number of movies that can be downloaded in a given week. As new movies get downloaded, an equal number of the oldest movies (based on the time stamp at the time of downloading) get deleted from the set-top box. If the household experiences low service quality in a given week, it would not receive all the scheduled movies; the movies that do not get downloaded in that week will never be available to the household.

The set-top box records the signal quality received by each household during each period on a scale of 0–2.4; our data contain this information.[6] The data were transmitted from the set-top box to the firm via a telephone line. A survey of 8% of subscribers showed that the number of movies received (a) was the most important factor affecting satisfaction with the service and (b) explained over 50% of the variation in satisfaction across subscribers. This implies that signal quality is an important determinant of the overall quality of the service. Furthermore, literature on service quality (e.g., Parasuraman et al.

[2] We elaborate on this later in §5.4.

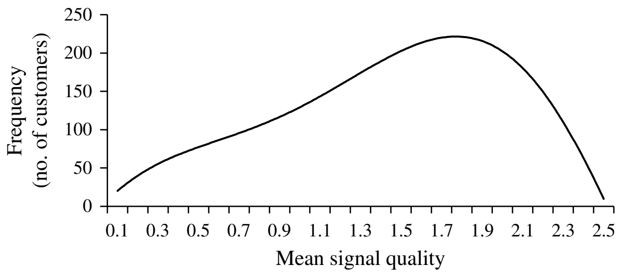
[3] The service was subsequently launched in a few other U.S. cities.

[4] Nam et al. (2010) use the same data to study the effect of word of mouth on customer acquisition. In contrast, the question in our paper pertains to how a customer's own experience with the service affects his or her retention conditional on having joined the service.

[5] Signal quality only affects the number of movies that are updated and not their picture or sound quality. In other words, if 30 movies are updated in a given month, all 30 movies will be of the expected quality.

[6] Conversations with the firm that provided these data revealed that a linear approximation of the signal quality on the 0–2.4 scale to the number of potential movies updated each month (i.e., 0–40) is reasonable.

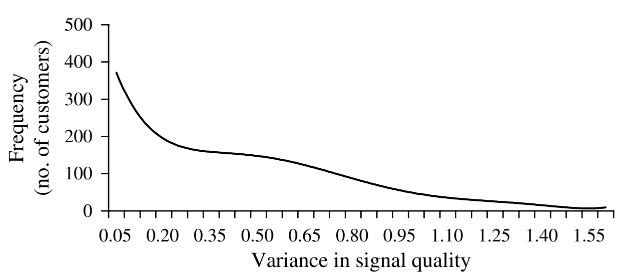
Figure 1 Distribution of Average Signal Quality Across Households



1988) has discussed the differences between objective quality of a service and customer perception. The strong correlation between the satisfaction scores and the signal quality as recorded in the set-top box suggest that this objective quality measure is a reasonable proxy for the perception of service quality. Therefore, for the remainder of the paper, we use the terms "quality," "service quality," and "signal quality" interchangeably.

Given that the signals are transmitted terrestrially, the average signal quality varies across households, depending on where they are located. To illustrate this point, we present the distribution of the average signal quality received by households in Figure 1. The figure suggests that there is considerable heterogeneity in signal quality across households, with some not getting any new movies during their tenure (i.e., average signal quality of 0). The average quality received by households was 1.415, whereas the median was 1.492. Furthermore, within a household, the signal quality could vary over time, depending on factors such as the weather, changes in the orientation of the antenna atop the set-top box, etc.—the average variance experienced by households was 0.447. However, there is significant heterogeneity among households in the extent to which they experience variability in signal quality. In Figure 2, we show the distribution of within-household variability in signal quality. Based on these descriptive analyses, we conclude that there is significant heterogeneity across households in average signal quality and its variability over time.

Figure 2 Distribution of Within-Household Variability in Signal Quality



Several aspects of the data make it well suited for our research. First, given that the set-top box records the signal quality received by households during each period, we are able to observe an important component of service quality over time. This helps us understand how the mean service quality and its variability are related to customer tenure. Second, the cross-sectional and temporal variation in signal quality is induced by factors such as household's location and weather conditions, respectively. As a result, the household cannot systematically alter the quality it receives. Furthermore, although the firm can make investments to improve the average quality *across all households*, it does not do so during the period of our study. Even if the firm makes such an investment, it cannot influence the level of quality received by a *particular household* in the market. Together, these factors allow us to treat signal quality as being exogenous to the subscriber.[7] This feature of the data allows us to measure the effects of quality without having to control for endogeneity or selection issues. Finally, the data contain information from the time of service activation for all households. This enables us to investigate how customers' beliefs about the service evolve over time as they obtain more information.

2.1. Data Patterns

In this section, we provide model-free evidence on how the mean and variance of quality influence retention rates. First, we discuss the marginal effects of mean and variability on termination and then consider the joint effects. Next, we document evidence that households learn about the quality of the service over time. We also present evidence that the rate of learning is related to the variance in signal quality experienced by these households.

2.1.1. Marginal and Joint Effects of Average Service Quality and Variability. It has been documented in the literature (see Bolton et al. 2006) that service termination (continuation) rates decrease (increase) with quality. In our data, the correlation between the binary outcome of termination (1)/continuation (0) for each household and that household's average signal quality over its tenure with the service is −0.29 and is statistically significant at the 5% level. In other words, households that, on average, receive higher signal quality terminate less than those receiving lower quality. As an alternative illustration of this relationship, we find that the average termination rates among households experiencing higher than median quality is lower than those experiencing low quality (11.4% versus 31.4%, significant at the 5% level), based on a median split.

[7] Nam et al. (2010) provide detailed evidence in support of the exogeneity of signal quality.

Table 1 **Interaction Effect Between Mean and Variability**

Termination rate		
	High signal variance (%)	Low signal variance (%)
High mean signal	14.6	10.0
Low mean signal	28.4	38.5

Next, we investigate the association between termination rates for households and the extent of variability in signal quality they experience. Once again, this is a cross-sectional association in which we correlate the binary household-level outcomes of termination/continuation with households' signal quality variances over their durations of service. Our data indicate a positive correlation of 0.09, which is statistically significantly different from 0 at the 5% level of significance. This shows that households experiencing higher variability in their service are more likely to terminate than those with low variability. In addition, we compare the average termination rates for households experiencing above versus below median signal quality variance. These results show that households with high signal quality variability tend to terminate more than those with low variability (18.5% versus 24.3%, significant at the 5% level). This relationship is consistent with aversion to variance or, more generally, risk aversion. To understand whether the effect of variability in service quality differs across average quality levels, we compare the termination rates at high and low levels of both mean and variance in signal quality. The results in Table 1 suggest an interaction effect of mean and variance: high variability is associated with higher termination rates at high mean quality levels; it lowers termination at lower quality levels.

To establish the above interaction effect more formally, we provide the results from a log-logistic hazard model in Table 2. The dependent variable in this analysis is the time to termination for each household and accounts for right censoring; i.e., some households might not have terminated the service by the end of the horizon. We include the average signal quality received, quality variance, and interaction between mean and variance as the key covariates in this analysis. Further, we control for heterogeneity by including household demographics as well as dummy variables for the month in which the household activates the service. The results reveal that all three covariates have statistically significant effects on time to termination. The results once again point to the presence of a significant interaction effect. Note that because of the presence of the interaction effect, we need to be careful in interpreting the coefficients. The negative main effect for variability implies that when the mean quality is low, variability lowers the termination hazard. On the other hand, when the mean quality exceeds 1.47 (i.e., 0.28/0.19), variability increases the termination hazard. This is consistent with the data patterns reported in Tables 1 and 2.

Table 2 **Results from a Termination Hazard Model with a Log-Logistic Baseline Hazard**

Dependent variable: *Time to termination/end*		
Variable	Coefficient	*t*-value
Mean signal quality	−0.62	−15.80
Signal quality variance	−0.28	−5.28
Interaction effect	0.19	3.51
Demographics	Yes	
Start period dummy	Yes	

Implication of Bounded Quality. As in most service applications, our service quality is bounded; in our context, the quality measure that translates to the number of movies downloaded lies between 0 and 2.4.[8] There are two potential concerns that arise because of the bounded nature of service quality. The first concern is that the lower bound implies that both low- and high-variability customers at the lower end of the quality spectrum are likely to have similar realizations of low quality outcomes. On the other hand, those with higher variability have more upside potential. Similarly, at higher quality levels, high-variability households have a higher probability of experiencing low quality outcomes than their low-variability counterparts. Hence, high-variability households are likely to receive more (fewer) movies than their low-variability counterparts at lower (higher) average quality levels. If this is true, the differences in average quality across households experiencing low versus high variability can explain the outcome in Table 1.

To evaluate the validity of this explanation, we need to compare the termination rates *after* controlling for the average quality experienced. In Table 3, we present the termination rates among low- and high-variability households on a fine grid of average quality. Comparing across the high and low variability levels at high average quality levels, we find that high variability leads to higher termination rates than low variability. However, comparing across variability levels at low average quality levels, we find the opposite; i.e., higher variability leads to lower termination rates at low average quality levels. In other words, high variability can increase termination rates

[8] In almost every service context, such as cell phone reception, service time at restaurants, and on-time arrival for airlines, quality is bounded. Even in instances where one might argue that the latent quality might be unbounded in the customer's mind, when we measure it in a managerially interpretable way (e.g., via surveys), the resulting quality metric will be bounded.

Table 3 Termination Rates at Various Levels of Average Quality

Low-variability households				High-variability households			
Avg. sig. quality	Number of households	% terminating	Tenure (months) conditional on terminating	Avg. sig. quality	Number of households	% terminating	Tenure (months) conditional on terminating
0.10	50	46	4.96				
0.24	68	47	4.69	0.27	12	33	8.0
0.41	65	58	4.97	0.41	75	40	6.77
0.58	40	70	5.0	0.58	114	34	6.67
0.74	36	61	4.50	0.76	144	33	7.0
0.92	45	69	5.42	0.93	186	33	6.98
1.09	42	50	4.29	1.09	209	27	5.96
1.26	58	14	6.0	1.24	208	24	6.78
1.42	104	16	5.71	1.42	220	17	8.16
1.59	157	13	6.15	1.58	237	13	7.52
1.76	222	11	7.38	1.74	153	15	7.22
1.92	264	14	4.71	1.91	84	15	9.31
2.08	256	9	5.29	2.05	17	24	9.75
2.25	214	14	4.67				
2.36	38	11	2.50				

at high quality levels but helps retain customers who experience low average quality.[9] Furthermore, note that households experiencing high variability stay with the service longer prior to termination compared to low-variability households. As we discuss subsequently, this pattern is suggestive of high variability deterring the ability of households to learn about the quality of the service they receive.

To further verify whether the bounded nature of quality is solely driving the interaction effect, we considered the termination rates among high/low average quality and variability levels for households that never experience signal quality at the bounds (i.e., 0 or 2.4). As in the full data, we observe that termination rates are lower among households experiencing high average quality and low variability. Moreover, the termination rates for all four groups in Table 4 suggest that there is an interaction effect: whereas high variability is associated with higher termination at high quality levels, the opposite is true at low quality levels. These patterns are similar to those reported in Table 1 for the full set of households. Therefore, we argue that the bounded nature of quality is not necessary for the interaction effect that we document. Thus, the mechanism by which higher variability lowers termination requires further investigation.

The second issue with bounded quality is that when the average quality is very high (low), variability is also likely to be low. This might hamper our ability to study the effect of variability at high or low average quality levels. In our data, although this is true for customers who receive very extreme values of average quality, for most of the quality range, there is a wide variation in variability. We illustrate this in two ways. First, consider Figure 3, where we present the average variance experienced by high and low variability at different average quality levels. The results in Figure 3 suggest that for the average quality levels experienced by 92% of households (except for those in the >2.25 range), there is considerable variation in variability. Second, consider the results in Table 3, where we present the number of households experiencing high and low variability on a very fine grid of quality levels. Barring the very low and high ends of the quality spectrum (average quality ≤ 0.1 and ≥ 2.25), we have high-variability households in all the remaining average quality levels. Therefore, there is a significantly large range of quality levels where an increase/decrease in average quality does not come at the expense of having very low variability.

Table 4 Interaction Effect for a Subset of Households Without Quality at the Bounds

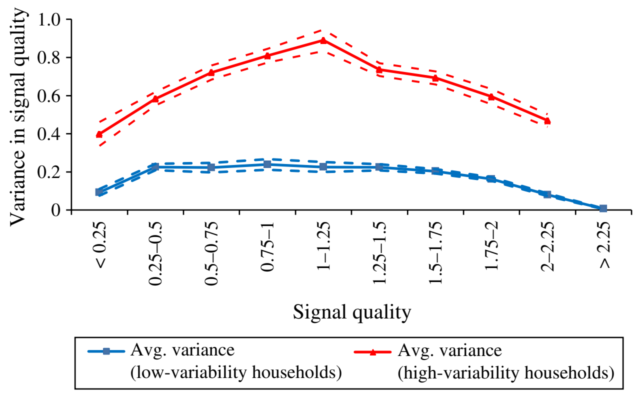
	Termination rate	
	High signal variance (%)	Low signal variance (%)
High mean signal	13	10
Low mean signal	23	29

Note. Without upper and lower bound: 1,588 households

2.1.2. Evidence of Learning. The above analysis considers the cross-sectional variation across households in our sample but it does not reflect how

[9] Note that the results in Table 3 just rule out the (obvious) explanation that the differential termination rate is due to differences in average quality. As the downside at the lower end of the quality spectrum is limited, households experiencing high variability are likely to receive higher signal quality, on average. However, these results do not say much regarding the necessity of formally modeling the bounded nature of signal quality. In §5.2.2, we formally account for the bounded nature of the data generating process.

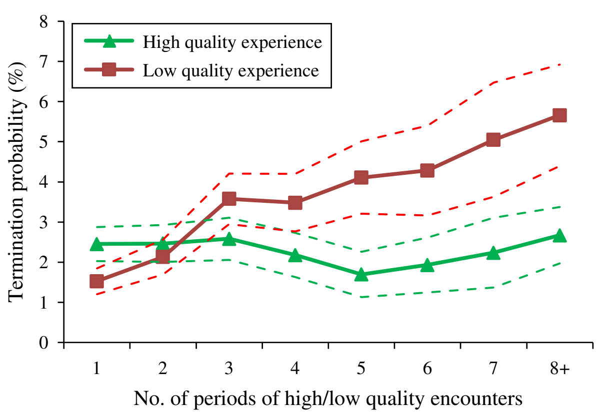
Figure 3 (Color online) Variability in Signal Quality at Different Average Quality Levels



Note. The dotted lines reflect the confidence interval for the estimate of the average variance for high- and low-variability households, respectively.

termination behavior varies based on the history of realized signal quality. If households are uncertain about the quality they receive, on average, the temporal variation in signal quality within a household would imply that a single realization is not sufficient to fully resolve this uncertainty. Rather, each realization provides a noisy signal of the true average quality being received by the household. Under these circumstances, households could learn over time about the true quality of the service they receive. In Figure 4, we plot the proportion of subscribers who terminate the service after receiving "n" periods of high quality signals or "n" periods of low quality signals for various values of "n." Here a "high" or "low" quality signal is defined as one that falls above or below, respectively, the median signal quality. The median is computed across signals received by all households over the data period. The figure shows higher termination rates among households receiving bad quality signals, with the effect becoming more pronounced with the number of periods for which

Figure 4 (Color online) Evidence of Learning: Termination Rates After Receiving a Certain Number of High vs. Low Quality Signals



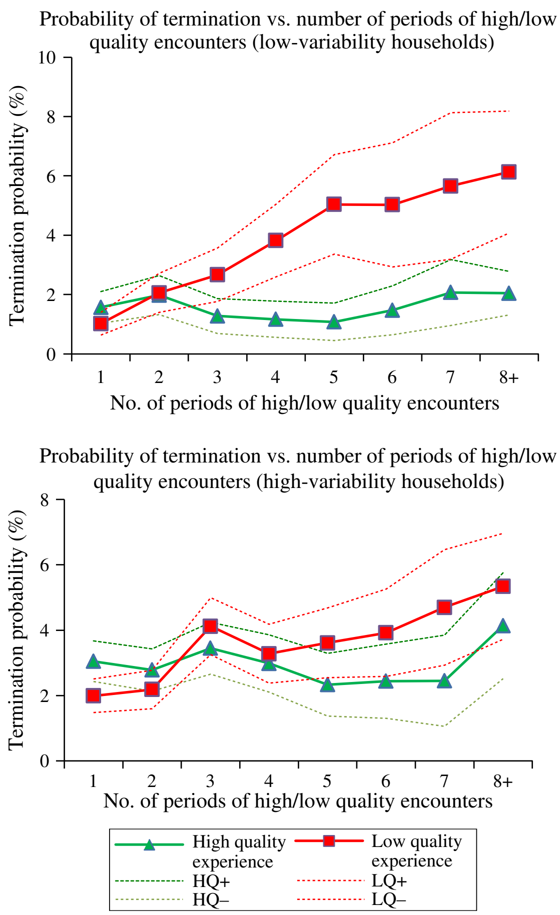
the quality is low. At the same time, termination rates decline slightly but do not appear to change much when households receive many periods of good signals. Together, these patterns seem to indicate that households learn about the quality they receive from the service over time.

Next, we look at how the patterns in Figure 4 vary by households subject to low versus high variability. These are depicted in Figure 5. This figure suggests that households that experience low variability and receive low quality signals over several time periods tend to terminate in higher proportions than households receiving high quality signals (i.e., there is limited overlap in their 95% confidence bands). However, there is no significant difference in termination rates based on the history of receiving low or high quality signals among households experiencing high variability (i.e., there is significant overlap in their 95% confidence bands). Together, these results suggest that the rate of learning is related to the variability in signal quality experienced by households. We conjecture that whereas low variability enables households to discern the true quality of the service, high variability renders such an inference difficult. In a Bayesian learning sense, this is likely to arise because households that experience high variability are likely to place a greater weight on the prior belief rather than on the signal.[10] Note that this inference is consistent with our earlier observation in Table 2 that households experiencing high variability stay with the service longer prior to termination compared to low-variability households.

In summary, our data patterns suggest that (a) termination decreases with average quality, (b) termination increases with variability, (c) there is an interaction effect between the average quality and variability, (d) customers learn about quality over time, and (e) the learning is hindered for households that experience high variability. Whereas (a)–(c) underscore the importance of both mean and variance, (d) points to uncertainty among households in the average quality they receive, and (e) probably suggests that the rate of learning is related to the variability that consumers experience. In the next section, we propose a model involving risk aversion and learning that reflects these factors. Subsequently, we will discuss alternative mechanisms that could rationalize our

[10] A more parsimonious account of the data that does not require Bayesian learning is that consumers use the information on the trajectory or slope of the most recent quality signals. Although the data are not reported here, we compared such models with the formal Bayesian learning model described in the model section. The Bayesian learning model yielded superior model fit, even after accounting for the additional parameters that needed to be estimated. We thank Dan Bartels and an anonymous reviewer for suggesting this alternative explanation.

Figure 5 (Color online) Evidence of Differential Learning Among Households Experiencing Low vs. High Variability



observed data patterns and compare them with our proposed mechanisms.

3. Model

3.1. Overview

We characterize the indirect utility that household h derives from subscribing to the service at time t as

$$\tilde{V}_{1ht} = \alpha_h + g(\tilde{Q}_{ht}) + \psi D_h + \tau S_t + \epsilon_{1ht}, \tag{1}$$

where α_h is the household's intrinsic preference for the service, $\tilde{Q}_{ht}$ is the household's belief about the quality of the service at time t, $g(\cdot)$ is a function that captures how quality influences the utility from subscribing, D_h are household-specific demographic characteristics that shifts the intrinsic preference for the service, and S_t are month dummies that capture seasonality in preference for the service. The term ϵ_{1ht} is an idiosyncratic shock experienced by household h at time t.[11]

[11] Technically, the utility is a function of the monthly subscription price. However, since there is no variation in the subscription price in the data, we cannot econometrically identify the price effect. As a result, the price effect is subsumed within the household's intrinsic preference.

A household's intrinsic preference for the service, α_h, and its responsiveness to average signal quality, β_h, are likely to be functions of the extent to which the household uses the service.[12] The rationale is that households that rent a lot of movies are likely to derive more consumption value from the service and thus find it more valuable. Similarly, high-usage households are also likely to be more sensitive to the quality of the service. We accommodate this feature in our estimation.

Since the household makes the subscription decision at the beginning of each period, it is uncertain about the quality of the service it will receive over the course of the month and whether it is worth the subscription fee. As discussed in the data section, there is significant heterogeneity across households in terms of the average quality of the service received. Therefore, it is conceivable that a household that is new to the service is uncertain about the average quality of the service that it will receive. Furthermore, there is temporal variation in quality experienced by a given household over time due to weather conditions. Therefore, the household is likely to be uncertain about (a) the average quality of the service it will experience and (b) the actual quality it will experience during period t for which it is making the subscription decision. Hence, the household's decision is based on the expected utility from subscribing, where the expectation is taken over the distribution of uncertainty. Formally, the expected utility that the household derives from subscribing to the service at time t is

$$\bar{V}_{1ht} = E[\tilde{V}_{1ht}] = \alpha_h + E[g(\tilde{Q}_{ht})] + \psi D_h + \tau S_t + \epsilon_{1ht}. \tag{2}$$

We assume that at time t, the uncertainty about the household's true quality is distributed $\mathrm{N}(Q_{ht}, \sigma^2_{Qht})$ and the temporal uncertainty is distributed $\mathrm{N}(0, \sigma^2_h)$. Therefore, the total uncertainty perceived by the household about the quality of the service at time t is the sum of the household's perceived uncertainty about the average quality of the service it receives (σ^2_{Qht}) and the temporal variation it experiences (σ^2_h); i.e., $\sigma^2_{ht} = \sigma^2_{Qht} + \sigma^2_h$. Over time, the household accumulates experience with the service and updates its beliefs accordingly. In what follows, we assume that households are Bayesian learners. Consequently, the mean converges to the true average quality received by the household, and the uncertainty (σ^2_{Qht}) converges to 0. However, temporal variation in signal quality experienced (σ^2_h) will persist.

[12] We thank the associate editor for pointing this out.

We normalize the observed (by the researcher) component of the per-period utility from not subscribing to the service to 0. Therefore, the total per-period utility from terminating the service, including the idiosyncratic shock, is

$$V_{0ht} = \epsilon_{0ht}. \tag{3}$$

We assume that the household-specific idiosyncratic shocks, ϵ, follow a type I extreme value distribution. The corresponding probability of subscribing is

$$\mathrm{Prob}_{ht} = \frac{\exp(\bar{V}_{1ht})}{1+\exp(\bar{V}_{1ht})}. \tag{4}$$

We recognize that since termination is, for the most part, an irreversible process, the household is likely to consider more than the current period utility while making the subscription decision. In §5.2.2, we consider an extension that accounts for this forward-looking behavior.

3.2. Risk Aversion

The expression for the expected utility will depend on the specification of the $g(\cdot)$ function. If $g(\cdot)$ is specified as a linear function of $\tilde{Q}_{ht}$, the expected utility will also be a linear function of the household's perception about the quality of the service, $\bar{Q}_{ht}$. Furthermore, the expected utility will be invariant to the uncertainty about service quality. As discussed in the previous section, our data suggest that households are averse to variability, on average. To capture this, we use a quadratic specification for $g(\cdot)$. We use the quadratic specification because researchers have used it in the past to effectively capture risk aversion (see, e.g., Erdem and Keane 1996, Ching 2010). Furthermore, it is computationally easier to estimate a model with quadratic utility as opposed to other functional forms, such as constant absolute risk aversion (CARA) (e.g., Chan and Hamilton 2006, Ching and Ishihara 2010, Crawford and Shum 2005), especially for the model that also accounts for forward-looking behavior (described in §5.2.2).[13] The corresponding expression for the expected utility in Equation (2) is

$$\bar{V}_{1ht} = E[\tilde{V}_{1ht}] = \alpha_h + \beta_h \bar{Q}_{ht} - \gamma \bar{Q}^2{}_{ht} - \gamma \sigma^2_{ht} + \psi D_h + \tau S_t + \epsilon_{1ht}. \tag{5}$$

Recall that $\sigma^2_{ht} = \sigma^2_{Qht} + \sigma^2_h$ is the total uncertainty perceived by household h regarding the quality of the service it would experience during period t.

[13] Although not reported here (available from the authors), results from the CARA assumption are very similar to those from the quadratic model when there is no forward-looking behavior.

3.3. Learning

We assume that households update their beliefs about the true quality of the service in a Bayesian manner. A household has a prior belief about the quality of the service at the time of activation. We assume that this prior belief follows a normal distribution such that $\tilde{Q}_{h0} \sim \mathrm{N}(Q_0, \sigma^2_{Qh0})$. (The prior belief also needs to be high enough that the household activates the service in the first place.) 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, e.g., Coscelli and Shum 2004), we assume that the quality of the signals that the household receives each period comes from a normal distribution with variance σ^2_h. In contrast to a majority of empirical studies, however, we as researchers observe the actual signal quality received by each household in each period.

Given the conjugacy of the prior belief 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

$$\bar{Q}_{ht} = \bar{Q}_{ht-1} + \frac{\sigma^2_{Qht}}{\sigma^2_{Qht} + \sigma^2_h}[Q_{ht} - \bar{Q}_{ht-1}], \tag{6}$$

where Q_{ht} is the actual signal quality 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

$$\sigma^2_{Qht} = \frac{1}{1/\sigma^2_{Qht-1} + 1/\sigma^2_h} = \frac{1}{1/\sigma^2_0 + \tau_{ht}/\sigma^2_h}. \tag{7}$$

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). Note that Equation (6) implies that the learning model essentially tracks the idea of updating last period's mean belief with the deviation of the current period's signal from that last period's mean belief. The influence of the deviation term, $[Q_{ht} - \bar{Q}_{ht-1}]$, which is $\sigma^2_{Qht}/(\sigma^2_{Qht} + \sigma^2_h)$, declines over time as the household converges to its true value.

3.4. Model Implications

The uncertainty experienced by households is likely to influence the expected utility from subscription in three different ways. First, from Equation (5), the expected utility is a decreasing function of the total uncertainty, $\sigma^2_{ht} = \sigma^2_{Qht} + \sigma^2_h$, because of risk aversion. Households that experience high variability in their signals (i.e., large σ_h^2) are more likely to terminate because of risk aversion compared to those with low variability. Second, the temporal variation in signal quality has an additional effect via Bayesian learning. From Equation (7), we can see that the rate at which a household's uncertainty about its average quality reduces as it accumulates information is a decreasing function of σ_h^2. Since the uncertainty about average quality (σ_{Qht}^2) enters the total uncertainty, $\sigma_{ht}^2 = \sigma_{Qht}^2 + \sigma_h^2$, the presence of high temporal variation in service quality is likely to have an additional adverse effect via risk aversion. Note that the posterior uncertainty about one's own average quality is bounded from above by the prior variance, σ_{Qh0}^2; i.e., $\sigma_{Qht}^2 < \sigma_{Qh0}^2$, $\forall\, t > 0$. Hence, if the prior variance is relatively small compared to the temporal variation, the second adverse effect of high variability has a limited impact on termination.

Third, Equation (6) suggests that the rate at which households update their beliefs about the true quality of the service will be a decreasing function of the variability in their signals (i.e., σ_h^2). Therefore, if two households have the same average quality in steady state, the household with lower σ_h^2 will converge to this quality faster than the one with higher σ_h^2. Thus, households that experience low variability are likely to be more responsive to quality than those with high variability; the weight on Q_{ht} in Equation (6) is larger for households with lower σ_h^2. This differential effect of quality as a function of variability faced by households is the mechanism by which our model rationalizes the interaction effect on termination.

Implication 1. *For new products or services where households are uncertain about the quality they experience, those experiencing low temporal variability in quality are likely to be more responsive (in terms of termination) to the average quality level compared to those experiencing high variability. This leads to an interaction effect between average quality and variability on termination.*

Since the households in our data set voluntarily signed up for the service, they must have had a high prior expectation about the quality of the service (or a very large positive shock at the time of activating the service, although this is less likely for all the subscribers). Moreover, the firm advertised the service based on the maximum number of movies that would be updated each week. Hence, we can reasonably assume that a majority of households have a prior belief that exceeds the true quality they experience.[14] Since households with higher values of σ_h^2 are likely to update their beliefs slowly, this learning deterrence would imply that they would stay with the service longer. However, learning deterrence is likely to adversely affect customer retention among households that receive higher signal quality vis-à-vis their prior belief about the service at the time of activation. Consequently, learning deterrence is likely to work in the same way as risk aversion for these households.

Implication 2. *The interaction effect between quality and variability will lead to lower termination rates among households experiencing high variability if these households have prior beliefs about the quality of the service that are higher than what they actually receive.*

When variability increases, so would the penalty from risk aversion. This would lower the utility from continuing with the service. At the same time, learning deterrence would imply that the utility from staying with the service would increase for households that have higher prior expectations than their true quality. The net effect of increasing variability would depend on the relative magnitude of these two factors. Equation (6) implies that the rate of learning deterrence is dictated by $\sigma_{Qht}^2/(\sigma_{Qht}^2 + \sigma_h^2)$, with lower values leading to slower updating. This function is bounded between 0 and 1 and becomes flatter as σ_h^2 increases. Therefore, if the average variability is very high, the marginal benefit of learning deterrence would be relatively small for both high- and low-variability households. Thus, the risk-aversion effect is likely to dominate when the overall service variability is very high. Consequently, the lower termination among high-variability households at low quality levels would cease to exist if the overall variability is very high. Nevertheless, we would still see an interaction effect in terms of differential responsiveness to quality improvements among low- and high-variability households.

Implication 3. *The interaction effect will lead to lower termination among households experiencing high variability only if the level of variability is not too high; if variability is very high, risk aversion will dominate and high variability will always lead to higher termination, even if the interaction effect exists.*

Implication 1 shows how the model can rationalize the interaction effect, and Implication 2 shows how this translates into the observed termination pattern, whereas Implication 3 highlights the boundary condition associated with the effect.

4. Estimation

4.1. Overview

In a typical learning model, there are four parameters of interest: (i) mean of the prior belief about the unknown entity (Q_0), (ii) prior variance (e.g., σ_{Qh0}^2), (iii) variance of the signals about the unknown

[14] We assess the validity of this assumption when we discuss the results.

entity (e.g., σ_h^2), and (iv) true value of the unknown entity (Q_h). Researchers typically estimate the true value of the unknown entity when they do not observe the exact signals received by the households.[15] Since we observe the signal strength received by individual households during each period, we do not estimate Q_h. We fix the signal variance, σ_h^2, based on the actual variance in signal quality received by the household. Note that this assumption is consistent with the model-free evidence that we presented earlier that the rate at which customers learn about the quality of the service (or the perceived precision of the experienced quality) is related to the variability that they experience; the rate of learning is slower in the presence of high variability.[16] Thus, the only components of the learning model that we estimate are the heterogeneous prior mean and variance about the signal quality.

In our application, we use city dummies, month dummies, income, number of children, and the number of elderly people in the household as the demographic characteristics that shift the intrinsic preference for the service. The city dummies pick up differences in unobserved characteristics of subscribing households across the three test markets.[17] With little loss in model fit, we discretized the continuous demographic variables by performing a median split with the high values coded as 1 and the low values coded as 0. Such a discretization is especially useful when extending the model to account for forward-looking behavior.

As previously discussed, we allow the parameters α_h (choice intercept), and β_h (responsiveness to signal quality) to vary with the household's itrinsic propensity to use the service. Although our data include information on the number of movies rented by each household over time, we cannot directly introduce the information directly into the model. This is because usage is an endogenous decision made by the household based on (a) the average quality of the service that it receives and (b) its intrinsic propensity to use the service. Rather, we need to isolate the intrinsic propensity of a household to use the service separately from the influence of signal quality and use this information in the model specification.

We accomplish this by using a two-step approach. In the first step, we regress the number of movies rented by each household during any time t, R_{ht}, on a flexible function of the average signal quality received by that household until t. Formally,

$$R_{ht} = \varpi_h + H(\bar{\hat{Q}}_{ht}) + \iota_{ht}, \tag{8}$$

where $H(\bar{\hat{Q}}_{ht})$ is a flexible function of $\bar{\hat{Q}}_{ht}$, the average signal quality experienced by household h until time t, and ϖ_h is the intrinsic propensity of the household to use the service, captured by household-specific fixed effects. The term ι_{ht} is an independent and identically distributed error term. In our empirical application, we specify $H(\hat{Q}_{ht})$ as a flexible third-degree-polynomial function of $\hat{Q}_{ht}$.[18, 19]

We allow for heterogeneity in the prior variance, choice intercept, and the signal quality effect. We model this unobserved heterogeneity using a latent class specification, with consumers belonging to different segments. Specifically, we assume that there are R segments of households such that the parameter vector, $\Theta^r = \{Q_{r0}, \sigma^2_{Qr0}, \alpha_r, \beta_r\}$, includes the set of heterogeneous parameters for segment r, $r = 1, 2, \ldots, R$. Based on Equation (4), the likelihood of observing the history of household h belonging to segment r can be written as

$$L_{hr} = \prod_{t=1}^{T_h} (\text{Prob}_{hrt})^{I_{ht}} (1 - (\text{Prob}_{hrt}))^{(1-I_{ht})}, \tag{9}$$

where I_{ht} is an indicator for whether the household subscribes to the service (1) or terminates (0). The corresponding overall likelihood for all households is

$$L = \prod_{h=1}^{H} \left(\sum_{r=1}^{R} \pi_h^r L_{hr} \right). \tag{10}$$

[15] In these situations, the information is assumed to come from a distribution with unknown mean and variance. The researcher would then simulate the information signals by making draws from this distribution, with the unknown moments of the distribution being estimated from the data.

[16] Another way of justifying this assumption is that households have experienced other terrestrial transmission methods, e.g., over-the-air television signals that have similar issues with variability. As those signals do not involve downloading, however, inferences regarding the average number of movies downloaded is still uncertain, although the variability is known. Subsequently, we verify the sensitivity of our key results to this assumption by incorporating uncertainty in this variance. We thank Andrew Ching for suggesting this explanation.

[17] Unobserved characteristics might arise from differences in the firm's advertising efforts across markets. If these differences in marketing effors are correlated with the average signal quality in these markets, not accounting for the unobserved characteristics is likely to yield biased estimates.

[18] Note that $\bar{\hat{Q}}_{ht}$ is different from $\bar{Q}_{ht}$ in the Bayesian model; the former captures the actual average signal quality received by household h until t, and the latter captures the household's perception about the average quality of the service at time t.

[19] A more general approach would be to formally model usage and subscription decisions as outcomes of utility maximizing behavior by households, with signal quality having a direct bearing on both decisions. Since the two decisions are temporally separated, the subscription decision would be a function of expected usage. Such a formulation will enable us to characterize the effects of both the intrinsic preference for the service and the usage propensity on the subscription decision. However, we believe such a formal treatment detracts from the main point of the paper, i.e., the effect on termination behavior of the interaction between the mean and variance in service quality.

In the above expression, π_h^r is the probability that household h belongs to segment r, $r = 1, 2, \ldots, R$ and L_{hr} is the likelihood for household h conditional on it belonging to segment r. Following the literature on concomitant variable latent class models (see Dayton and Macready 1988, Gupta and Chintagunta 1994), we allow the probability that household h belongs to segment r, π_h^r, to be a function of the household's intrinstic propensity to use the service, ϖ_h. Specifically, we have

$$\pi_h^r = \frac{\exp(\lambda_r + \chi_r \varpi_h)}{1 + \sum_{r'=1}^{R-1} \exp(\lambda_{r'} + \chi_{r'} \varpi_h)}, \tag{11}$$

where $\{\lambda_r, \chi_r\}$ are parameters to be estimated. For identification, we set the parameters of the Rth segment to zero.[20]

4.2. Identification

In most common applications of learning models, researchers estimate the prior mean and the signal variance and fix the prior variance to 1 for identification (see, e.g., Narayanan et al. 2005). As previously discussed, since we use the signal variance information from the data, we can infer the ratio of the signal variance to the prior variance and, consequently, the prior variance based on the rate of learning; a lower ratio is synonymous with faster learning. The challenge is to identify the prior mean separately from the prior variance; a household can hold a high posterior belief after receiving low quality signals either because it started off with a high prior belief or because it perceives a very low prior uncertainty. There are two arguments for the identification of the prior mean separately from the prior variance. First, unlike in most common applications, we observe the signal quality. This additional information allows us to characterize the evolution of the posterior belief conditional on the prior mean and variance precisely; in scenarios where we do not observe the actual realized signals, we need to estimate the mean of the underlying distribution from which signals are generated and integrate over this distribution to derive the posterior belief. Second, the identification of the prior mean separately from the prior variance is enabled by the functional form of the Bayesian learning model. Specifically, as a household accumulates more information, its posterior belief becomes more precise. As a result, the household becomes progressively less prone to updating its beliefs in response to realized signals. Since the evolution of the posterior variance is governed by a specific functional form (as in Equation (7)), we are able to identify the prior mean separately from the prior variance. Thus, identification is partly based on the functional form of the learning model.[21]

In addition to the prior mean and variance, we estimate the following parameters: the intrinsic preference for the service, α_h; effect of perception about signal quality, β_h; effect of demographic characteristics, ψ; 11-month fixed effects, τ; and, more importantly, the risk-aversion parameter, γ. As previously noted, one of the unique aspects of the paper is the ability to estimate the risk-aversion parameter γ. There are two sources of variation that enable us to identify the risk-aversion parameter. The first is the cross-sectional difference in variability in service quality experienced by households. From Equation (4), we can see that as the posterior variance $\sigma_{Qht}^2 \to 0$ over time via learning, the total uncertainty experienced by household h, $\sigma_{ht}^2 \to \sigma_h^2$. Since we observe the variance of quality received by individual households, σ_h^2, differences in variability experienced by households allow us to identify γ. Second, as households accumulate information about the quality of the service over time, their posterior beliefs become more precise. The rate at which this precision increases would depend on the precision of the information, $1/\sigma_h^2$. This temporal and cross-sectional variation in σ_{Qht}^2 further strengthens the case for identification of the risk-aversion parameter. In contrast, previous research (see, e.g., Crawford and Shum 2005) has had to base identification of the risk-aversion parameter only on the temporal variation in posterior variance, σ_{Qht}^2, which is not directly observed by the researcher.

5. Results

5.1. Overview of the Results

We began our estimation by identifying the optimal number of segments in the heterogeneity distribution. To this end, we first estimated models with one, two, and three segments. Based on the Bayesian information criterion (BIC), we identified the two-segment solution as the best. We present the estimates in Table 5. Recall that in our empirical specification, we characterize segment membership probabilities as functions of each household's intrinsic propensity to use the service. Based on the posterior segment membership probabilities, we assign each household to one of the two segments. We present information on the size, composition, and characteristics of the two segments in Table 6.

[20] An alternative approach would be to let α_h and β_h be linear functions of ϖ_h, such that $\alpha_h = \bar{\alpha} + \zeta_\alpha \varpi_h$ and $\beta_h = \bar{\beta} + \zeta_\beta \varpi_h$. However, such a formulation would add an additional state dimension when extending the model to one with option value. Further, there could be a concern with any residual endogeneity in usage if we directly introduce the fixed effects into the utility function. The results from the myopic version of the model yielded very similar substantive results under the proposed and alternative formulations.

[21] We would like to thank an anonymous reviewer for suggesting this identification strategy.

Table 5 Model Estimates

Parameter	Estimate	Std. error
Intercept (segment 1)	1.386	0.494
Intercept (segment 2)	−7.013	1.283
Signal quality effect (segment 1)	4.044	0.357
Signal quality effect (segment 2)	7.558	0.815
Risk aversion (exp(·))	0.200	0.101
October	−0.284	0.127
November	1.725	0.509
December	0.176	0.215
January	0.255	0.196
February	0.608	0.146
March	0.277	0.177
April	0.259	0.170
May	0.078	0.156
June	−0.158	0.142
July	−0.246	0.131
August	0.023	0.140
Salt Lake City	0.402	0.094
Spokane	0.532	0.146
Income	0.397	0.085
Child	0.006	0.098
% old	0.074	0.095
Signal quality prior variance (segment 1) (exp(·))	−2.463	0.383
Signal quality prior variance (segment 2) (exp(·))	−2.500	0.296
Transformed prior mean (segment 1)	0.790	0.375
Transformed prior mean (segment 2)	10.296	0.034
Segment 1 membership parameter (intercept)	1.532	0.277
Segment 1 membership parameter (effect of intrinsic propensity to use the service)	−0.221	0.039
Log-likelihood	−3,008.511	

The results from Table 6 imply that segment 1 is the larger of the two, with approximately 80% of the households, whereas segment 2 accounts for the remaining 20%. Households in segment 1 have a relatively higher intrinsic preference, but they are less responsive to signal quality compared to segment 2. Nevertheless, as expected, both segments respond positively to signal quality.

Our estimate of the risk-aversion parameter is 1.22 (standard error = 0.427). We restrict the risk-aversion term to be positive by exponentiating the corresponding parameter. The statistically significant risk-aversion parameter corroborates the pattern in the raw data that, on average, high variability in signal quality is associated with higher probability of termination.

Table 6 Segment Characteristics

	Segment 1	Segment 2
Segment size	2,602	644
Signal quality prior mean (estimated)	1.651	2.4
Signal quality prior variance (estimated)	0.086	0.090
Mean monthly rental (usage)	3.013	4.364
Average signal quality	1.46	1.19
Variance in signal quality	0.447	0.449
% terminating	6	82

The results in Table 5 imply that the probability of belonging to segment 1 decreases with the propensity to use the service (ϖ_h). This intuition is reflected in the results in Table 6, which suggest that households in segment 2 use the service more than those in segment 1. However, despite their higher propensity to use the service, households in segment 2 terminate the service at a higher rate than those in segment 1. The low value of the intercept for this segment suggests that households in this segment derive a very low intrinsic utility from the service (after accounting for usage), although they derive a high consumption utility (since, as we note above, segment 2 households have a higher propensity to use the service).[22] The low intrinsic utility for segment 1 could be a result of characteristics such as poor match value and low convenience.[23] Furthermore, as we discuss below, households in segment 1 experience higher average signal quality compared to those in segment 2 (1.46 for segment 1 versus 1.19 for segment 2), which can also partly explain the higher termination rates among segment 2 households. However, there is no difference among the segments in terms of the variance in signal quality that they experience.

The results from Table 6 suggest that households in segment 2 have a prior belief that they will receive the maximum signal quality of 2.4 (standard error = 0.072).[24] Relative to this prior belief, households in this segment experience average signal quality of 1.19. On the other hand, households in segment 1 have lower prior beliefs, at 1.65. In contrast, these households experience average signal quality of 1.46. Therefore, on average, households in both segments have higher prior beliefs than the actual quality that they receive. Recall that per Implication 2, the interaction effect between quality and variability will lead to lower termination rates among households experiencing high variability if these households have prior beliefs about the quality of the service that are higher than what they actually receive. Therefore, our results seem to rationalize the observed data patterns.

[22] In the alternative formulation, where we can characterize the intercept as $\alpha_h = \bar{\alpha} + \zeta_\alpha \varpi_h$, we can parse out the intrinsic utility from the service ($\bar{\alpha}$) separately from the consumption utility, $\zeta_\alpha \varpi_h$. Although not reported here, the main substantive results are very consistent across these two alternative formulations of how the parameters of the utility function are related to the intrinsic propensity of a household to use the service.

[23] Households that have high usage do not necessarily have a high match value; they may just have a high taste for watching movies, but may still not be excited about the assortment of movies offered by the service.

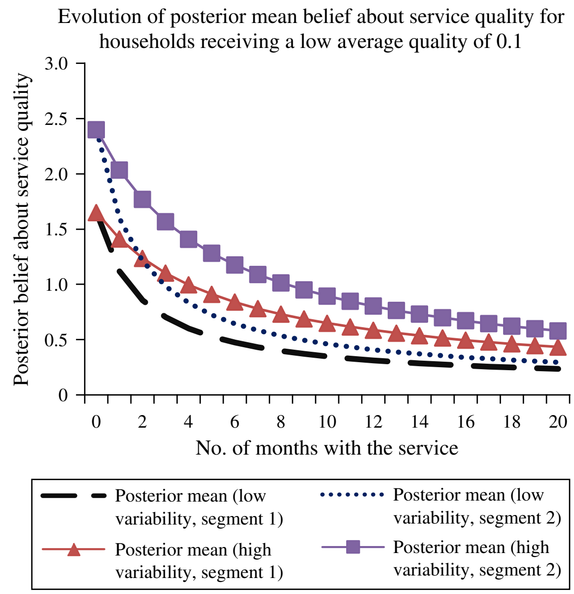
[24] To restrict the estimated prior mean to lie in the range of 0–2.4, we use a logit transformation such that $Q_{r0} = 2.4(\exp(\varrho_r)/(1+\exp(\varrho_r)))$, where ϱ_r can take any value between $-\infty$ and $+\infty$. The estimates reported in Table 4 correspond to ϱ_r, whereas those reported in Table 5 are Q_{r0}.

The estimated variances for the prior belief (i.e., uncertainty in the prior) are fairly consistent (in the range of 0.086–0.09) across the two segments. Note that we restrict the variances to be positive by exponentiating the estimated parameters. Hence, the parameters reported in Table 4 are the logarithms of the variance terms. As discussed in §3, the rate at which households update their prior beliefs about signal quality via learning would depend on the relative magnitudes of the variability in the signals that they receive vis-à-vis the prior variance. The average variances in signal quality experienced by low- and high-variability households (defined based on a median split) were 0.075 and 0.372, respectively. Given that the signal variance for high-variability households is higher than the estimates for the prior variance, these households are likely to be slow in updating their beliefs about signal quality over time.

We illustrate the relative rate of learning among low- and high-variability households implied by these estimates in Figure 5. As in the data, we assume that the low-variability household perceives a variability of 0.075, whereas the high-variability household perceives a variability of 0.372. To illustrate the differential rate of updating the prior belief, we consider two identical households (low and high variability, respectively) that receive a low average quality of 0.1 in Figure 6. These results suggest that there is a marked difference in the rate of updating between the low- and high-variability households. For example, whereas the low-variability household in segment 2, starting with a prior of 2.4, would update its belief about the average service quality to less than 1 within three periods, it would take the high-variability household nine periods to do so. Consequently, high-variability households consistently have higher beliefs about the quality of the service compared to those experiencing low variability. As is evident from the trajectory of the posterior mean for households in segment 1, which start with a much lower prior belief of 1.65, this result holds whenever the prior belief is higher than the actual quality. However, at high quality levels, the benefit from learning deterrence is very small, and is likely to be offset by the higher risk aversion.

A typical test for the validity of a model is its ability to replicate key patterns in the data. As motivated throughout the paper, a key pattern of interest is the differential effect of variability in service quality on termination rates among households receiving low versus high quality. To verify that the estimates from both versions of the model can indeed replicate these patterns, we simulated the termination probabilities for the same groups of customers. We present the results from this simulation along with the corresponding patterns in the raw data in Figure 7. These results suggest that our model estimates are able to replicate the interaction effect between signal quality mean and variability on termination.

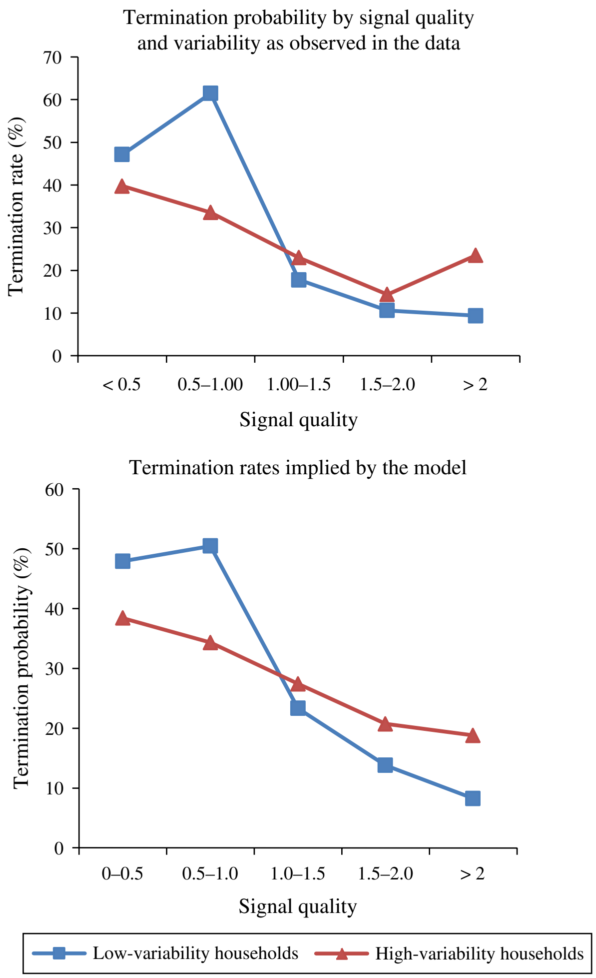
Figure 6 (Color online) Implication of the Model Estimates



5.2. Alternative Specifications and Model Extensions

5.2.1. Alternative Specifications. We compare the proposed model with two other alternative specifications. The first alternative specification is based on Bolton et al. (2006), who propose that variability can increase customer retention if the variation results in extreme positive experiences. This is an appealing explanation for the lower termination rates among high-variability households that experience low quality, on average. To test whether this alternative explanation can yield a superior fit, we estimated a model where we specified the utility that a household would derive from subscribing to the service at time t as a function of (a) the average quality experienced by a household until the previous period, (b) the number of extreme positive signals (defined as >2) received till time t, and (c) the number of extreme negative signals (defined as <0.5) received till time t. In addition, as in the proposed model, we included controls for demographic characteristics and seasonality. Note that the specification with the average quality experienced until the previous period is similar to a learning model with a very diffuse prior belief about the quality of the service. The alternative model fit the data worse than the proposed model in terms of log-likelihood (LL) ($-3{,}104.63$ versus $-3{,}008.51$) and BIC (6,474.58 versus 6,293.0). In addition, we estimated a more refined version of the above specification by including the "gain" and "loss" of the most recent signal received relative to the mean signal quality until that period. The

Figure 7 (Color online) Termination Rates in the Data and Those Implied by the Model Estimates



rationale is that if households are learning about the quality of the service based on their experience, the average quality till date would capture such learning. The positive (negative) deviations can be construed as gains (losses) relative to this perceived quality. But even with the added flexibility, this model could not explain the data as well as our proposed specification (LL = −3,037.70; BIC = 6,320.72).

The second alternative rationalization for the lower (higher) termination among high-variability households experiencing low (high) average quality is that the customers are risk seeking at low quality levels and risk averse at the higher end of the quality spectrum.[25] Consequently, a convex utility at lower quality levels and a concave specification at high quality levels should be able to explain the data patterns. To verify if this alternative specification can explain the data better than the proposed model, we estimated a flexible version of the model with risk aversion but without learning (as in Equation (4)). We impart the additional flexibility by allowing the risk-aversion parameter, γ, to vary based on whether the household receives low/high quality (defined based on a median split), on average. As in the above specification, we characterize the household's belief about the quality of the service in any given period using the average quality experienced by the household until the previous period. This alternative specification with flexible risk aversion did not fit the data as well as the proposed model (LL = −3,121.16; BIC = 6,487.634). Although our discussion thus far has been on the relative fit of these two alternative explanations vis-à-vis our proposed structure, it is worth noting that these alternative accounts also cannot generate the specific implications that our model provides. Thus, the value of the proposed model is more than just being able to rationalize the data better.

[25] We thank Victor Aguirregabiria and Sanjog Misa for suggesting variations of this explanation.

5.2.2. Model Extensions.

(a) *Consideration of Option Value.* The presence of learning implies that as a household accumulates more experience with the service, its belief about the quality gets more precise (i.e., $\sigma^2_{Qht} \to 0$ in Equation (6)). 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 (Erdem and Keane 1996, 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. We present details of the model that accounts for option value as well as the appropriate estimation strategy in Online Appendix A (online appendices available as supplemental material at http://dx.doi.org/10.1287/mnsc.2014.2105).

We estimated the forward-looking model by fixing the discount factor at 0.99. We discuss the results from this analysis in the online appendix. Notably, the forward-looking model fit the data slightly better than the myopic version (log-likelihood of −2,995.16 for the forward-looking model versus −3,008.5 for the myopic model). Furthermore, the forward-looking model yielded results that were similar to the myopic version in terms of the direction of the parameter estimates and the composition and characteristics of the two segments (see the online appendix for results). More importantly, the forward-looking model was able to replicate the same key data patterns as the myopic version. Nevertheless, as the myopic version of the model was adequate in describing the data patterns, we appeal to model parsimony and focus on the myopic version of the model. We note that in problems such as those studied by Lin et al. (2015), one might be able to simplify the solution to dynamic problems that could, in turn, allow for easier consideration of dynamics.

(b) *Accounting for Bounded Signal Quality.* As in many other scenarios where researchers have considered learning, the entity about which households update their beliefs, i.e., mean signal quality, is bounded; in our context, the signal quality (number of new movies downloaded) is bounded between 0 and 2.4 (40 per month).[26] However, in view of empirical tractability, we follow the precedence in the Bayesian learning literature by assuming a normal distribution for the realized signal quality.[27] Although this side steps the issue of the bounded nature of the data, basing our model on more general nonconjugate distributions would render it empirically and analytically intractable.[28] In view of this trade-off, we formulated an empirical strategy that accounted for the bounded nature of signal quality, while retaining conjugacy. We accomplish this by defining an underlying latent signal quality that is unbounded and can thus be treated as normally distributed. Households learn about this latent variable through their experience.

We tried two alternative specifications for how the latent quality affects the utility that a household derives from subscribing the service. In the first formulation, we assume that although households learn about the quality of the service in the latent, unbounded space, their subscription decision would depend only on the corresponding signal quality that is bounded between 0 and 2.4. We impose these bounds by treating the realized signal as a censored outcome of the underlying latent variable. The approach requires us to transform the latent posterior belief into the corresponding expected quality and variance that would eventually affect the subscription decision.

In the second approach, we assume that the household's utility is a function of the latent quality, not the observed, bounded values. Further, we relax the assumption that within the bounded space, the latent quality is the same as the measured quality. 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 and the signal scale parameter that translate the observed bounded signal to the unbounded space. We provide details of these two model formulations and estimation in Online Appendix B.[29]

We present the results from the myopic version of this model in Online Appendix B. Overall, the key results regarding the presence of two distinct segments and evidence of risk aversion are similar to those from the model that does not account for the bounded nature of our data. Furthermore, the estimates were able to replicate the key aspects of our data, namely, the differential effect of variability in service quality on termination rates among households receiving low versus high quality. However, both model formulations yield inferior fit (log-likelihood of $-3{,}016.18$ and $-3{,}010.46$) compared to the model that does not account for the bounds ($\mathrm{LL} = -3{,}008.51$). Therefore, the rest of our discussion below is based on the latter estimates.

(c) *Uncertainty and Learning About Signal Quality Variability.* Our empirical specification assumes that the perceived precision of the information that households accumulate as they gain experience with the service. Our model-free evidence suggests that the rate at which households respond to the cumulative information about the quality of service is inversely related to the actual variance they receive. In view of this evidence, we fix the signal precision for each household, $1/\sigma_h^2$, as the inverse of the actual variance in signal quality received by them. Nevertheless, we have made a specific assumption that the precision of the information that the customers perceive is the same as the actual variability they experience. As a robustness check, we estimated a model that allowed households to be uncertain about the variance (or precision) of the information that they accumulate. We operationalized this uncertainty about variability by using a discrete distribution with two supports.[30] The

[26] In our data, there are 4,715 (out of 27,486) observations when the signal quality is potentially bounded from below; i.e., we observe 0 signal quality. In contrast, there are only 18 observations where the signal quality is 2.4. Therefore, being bounded from above is less of an issue.

[27] A possible rationalization for this formulation is that a bounded rational consumer may subconsciously use a simplified rule to update her beliefs (see Lin et al. 2015 for a similar rationalization). The idea is that a consumer receives latent noisy signals that are normally distributed (e.g., the quality signal could be a function of multiple factors, such as perceived movie qualities, number of movies being downloaded, etc.). Such noisy signals could be highly correlated with the observed bounded signals, which correspond to the number of movies being downloaded. The consumer might prefer to use the observed bounded signals to update her prior belief because they are more salient. The conjugate prior updating rule, although not strictly "correct" when encountering the bounded signals, is easy to apply. We thank an anonymous reviewer for suggesting a cogent articulation of this rationalization.

[28] In some instances, we can use some naturally bounded conjugate distributions such as beta-binomial to characterize the bounded nature of our data. However, the expressions for the mean and variance in this family are related to each other. This runs counter to our data wherein we have households experiencing different combinations of mean and variance.

[29] Grubb and Osborne (2015) use a similar approach based on the censored normal distribution and Bayesian learning.

[30] Consistent with the model-free evidence that rate of learning is inversely related to the variability experienced by a household, we

results from the myopic version of the model revealed that the substantive results remained unaltered with this augmentation.

The above model assumes that households do not learn about their true variance over time; rather, they know the distribution of variance and account for that in their behavior. A more complete specification would entail allowing for households to also learn about this variance. A natural approach to accommodating such behavior in a computationally tractable way would entail exploiting the conjugacy of the normal and inverse gamma priors for the mean and variance, respectively (Gelman et al. 2000, Zhao et al. 2011). However, the assumption in this approach that the rate of learning would not depend on the precision of the information (signals) is not consistent with our data.[31] This is inconsistent with our proposed mechanism (motivated by data patterns) that the rate of learning is influenced by the variability in signals received.

5.3. Implications

Earlier, we laid out three implications of the model. In this section, we demonstrate them numerically, based on the parameter estimates discussed above. Implication 1 suggests that the households with low variability should be more responsive to changes in the quality of the service compared to those experiencing high variability. To demonstrate this, we simulated the termination probabilities when signal quality is higher by 1%. We present these results for different mean levels and variability in quality in Table 7. Consistent with the positive effect of signal quality, the termination rates decrease for all groups. More importantly, the effect is much stronger for households experiencing lower variability, both in absolute and percentage terms. Notably, the average signal quality elasticity for low-variability households is significantly higher at -1.88 (standard error $= 0.22$), compared to -0.51 (standard error $= 0.13$) for households experiencing high variability in signal quality.

Implication 2 suggests that the extent to which termination rates are lower among high-variability households would depend on their prior belief vis-à-vis the actual quality that they experience. Specifically, since the lower termination rates among households experiencing high variability accrues due to learning deterrence, it can only happen if the prior belief is higher than the true quality they experience. We

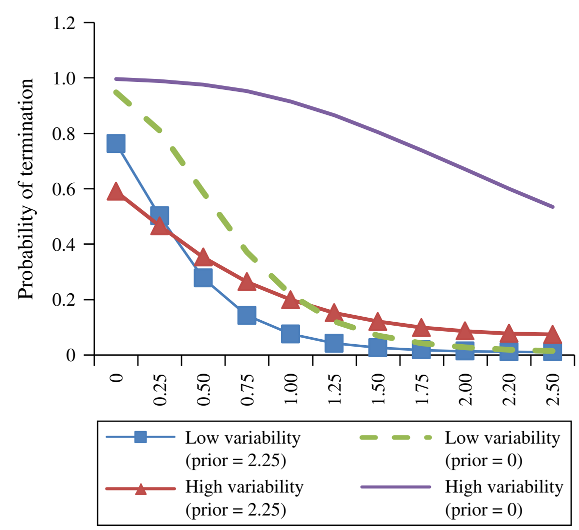
Table 7 **Effect of a 1% Increase in Signal Quality on Termination Rate**

	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	−0.38	−0.07	−0.78	−0.17
0.5–1	−0.44	−0.09	−0.88	−0.26
1–1.5	−0.23	−0.12	−0.98	−0.42
1.5–2	−0.21	−0.12	−1.52	−0.57
> 2	−0.06	−0.12	−0.75	−0.64
Average	−0.20	−0.11	−1.10	−0.41

demonstrate this via counterfactual analyses wherein we assume values of parameters that are similar to the model estimates and simulate the termination probabilities for different values of priors. Specifically, as in the data, we assume that (scaled) true quality can be in the range of 0–2.5 with households experiencing quality levels in increments of 0.25. We simulate the termination probabilities under two scenarios: prior belief $= 0$ and 2.25. We present the results from this analysis in Figure 8. When the mean of the prior belief is 2.25, learning deterrence lowers termination rates among low-quality households. Thus, high-variability households have lower termination rates at low quality levels compared to their low-variability counterparts. On the other hand, when the mean of the prior belief is 0, high-variability households always have higher termination rates. Nevertheless, the interaction effect arising due to differential responsiveness to service quality still exists.

To demonstrate that the lower termination due to learning deterrence occurs only at quality levels lower than the prior, we plot the difference between the learning components of utility (i.e., $\beta_h \bar{Q}_{ht} - \gamma \bar{Q}_{ht}^2$ from

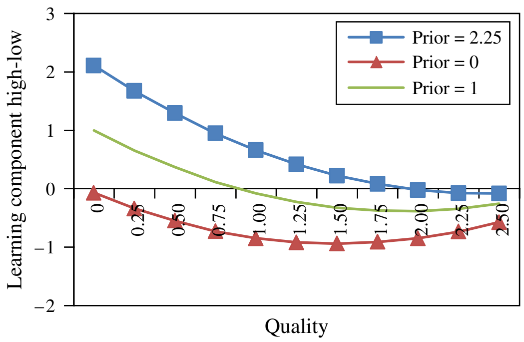
Figure 8 **(Color online) Effect of Prior Belief and Variability on Termination Probabilities**



assume that the mean of this distribution of uncertainty for each household is the same as the actual variance that they experienced.

[31] This is evident from Equation (13) in Zhao et al. (2011) wherein the posterior belief is independent of the variance of the signal. Our empirical calibration of such a model could not replicate the differential effect of variability in service quality on termination rates among households receiving low versus high quality.

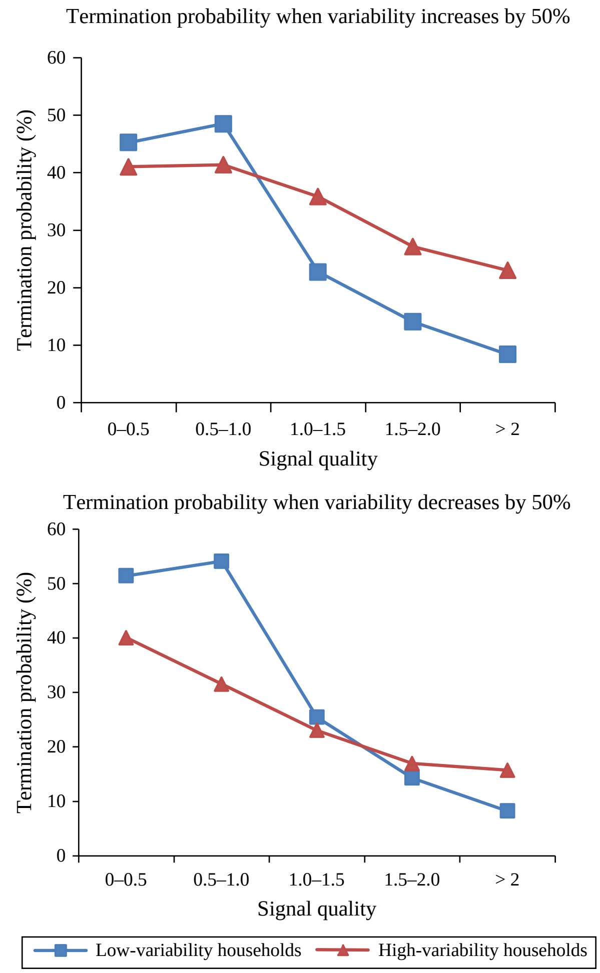
Figure 9 (Color online) Difference Between the Learning Component of Utility for High- and Low-Variability Types



Equation (4)) for High- versus low-variability households in Figure 9. Positive values imply that the learning component for the high-variability types is higher than that for the low-variability types. The results reveal that when the prior mean is 2.25, the difference in the learning component of utility is positive throughout. As the prior decreases, it becomes progressively more negative over a large range of qualities; i.e., learning deterrence will increase termination if households have a lower prior belief compared to their true quality. Together, these results reinforce the intuition that learning deterrence is likely to lower termination only among households that believe that the quality of the service is better than it actually is.

Implication 3 predicts that the range of average quality levels at which the termination rates among high-variability households is lower than their low-variability counterparts would diminish as the level of variability (σ_h^2) increases for all customers. But if the variability is lower, we would observe lower termination among high-variability households over a larger range of quality levels. In Figure 10, we present termination probabilities when variability increases/decreases by 50% for all households. When variability decreases by 50%, the two lines intersect at the average quality bin of 1.5–2. Note that this is higher than the point of intersection under status quo, i.e., the average quality bin of 1–1.5 (as in Figure 7). Therefore, when variability is decreased, termination rates would be lower among high-variability households (compared to their low-variability counterparts) over a larger range of quality levels. Yet when variability is increased by 50%, the two lines intersect in the 0.5–1 average quality bin, which is lower than the point of intersection under the status quo. As an extreme outcome, when variability increases by 82%, we would not see the high-variability households having lower termination rates at low quality levels, although the interaction effect in terms of differential responsiveness to quality among low- and high-variability households would still exist.

Figure 10 (Color online) Termination Probabilities When the Overall Variability Changes by 50%



5.4. Managerial Implications: Relative Effects of Increasing Mean Quality vs. Lowering Variability on Termination

Our research has three important managerial implications. First, the interaction effect between the average service quality and variability on customer retention suggests that managers need to consider the latter while inferring the returns to improvements in average quality. In particular, in our data, we find that ignoring the interaction effect between average quality and variability leads to an 18%–64% (5%–31%) overestimation (underestimation) of quality improvement elasticities among high-variability (low-variability) households.[32] Although it is common practice in the service industry to consider

[32] These elasticity estimates are based on a logit model that linked retention/termination to average quality and variability experienced by a household, as well as their interaction. In addition, we controlled for a household's intrinsic propensity to use the service and demographic characteristics. We estimated two versions of the model: (a) a cross-sectional version that considered whether a household terminates the service at the end of the data and

the average quality experienced by customers (e.g., average wait time in quick service restaurants, percentage on-time arrival for airlines), variability is seldom reported. In many instances, managers may have access to information on the quality experienced by individual customers over time, which enables them to determine variability. For example, cell phone service providers can potentially track the numbers bars or dropped calls experienced by individual customers over time. We argue that such variability measures can be instructive in employing the appropriate customer retention efforts.

The second managerial implication is that the interaction effect implies that customers experiencing high variability are likely to be less responsive to improvements in average quality. This is evident from the results in Table 7, which show that households experiencing low variability exhibit higher elasticities (elasticity of −1.1 versus −0.41 for high-variability households) to quality improvements in terms of reduction in termination rates. As a result, improvements in average quality that are targeted toward customers experiencing low variability is likely to yield higher returns in terms of customer retention.

Our empirical analysis suggests that there are two possible levers that managers can employ to increase customer retention, especially at the higher end of the quality spectrum: increase average quality and/or lower variability. For the third managerial implication, we perform counterfactual analyses to understand the relative efficacy of these two alternatives in lowering termination.[33] Clearly, at low quality levels, where lowering variability can increase termination, managers need to focus on increasing average service quality. On the other hand, at intermediate and high quality levels, both lowering variability and increasing average quality are viable options. In our counterfactual analysis, we determine the increase in average number of movies that can accomplish the same reduction in termination as lowering the standard deviation by one movie. These results suggest that for households experiencing low variability, increasing the mean is always a better option at average quality levels < 2. For households that experience average quality greater than 2, we need to increase the average number of movies by 0.7 to achieve the same reduction in termination as lowering the standard deviation by one movie. If the cost of increasing the average quality by one movie is the same as the corresponding cost of lowering the standard deviation by one movie, the former is a more attractive option for low-variability households.

However, the results are partly different for households experiencing high variability. We find that at intermediate quality levels, increasing the mean is as effective as lowering the standard deviation (increasing the mean by 1.12–1.7 movies is equivalent to lowering the standard deviation by 1 movie). But at high quality levels, a much larger increase in the mean number of movies (increase in average quality $= 2.25$ movies at the average quality of 1.5–2) is needed to achieve the same lower termination as lowering standard deviation by one movie. In fact, at very high quality levels, the required increase in quality would take the number of movies beyond the feasible range. This happens for two reasons. First, the concavity of the utility function implies that the marginal effect of increasing the mean decreases as quality increases. Second, the marginal benefit of lowering the standard deviation by one movie is higher at high quality levels. Given that low-variability households are (a) more responsive to quality and (b) yield lower benefit from lowering variability, increasing quality is likely to be more effective in lowering their termination than for the high-variability households. Overall, these results imply that at very low quality levels, increasing mean quality can be effective in lowering termination. In contrast, at high quality levels, lowering variability is likely to be more effective.

The implications of these results go beyond our application; Knutson (2013) highlights the importance of the trade-off that we investigate. Although Verizon has been successful in rolling out its 4G LTE service more widely across the United States than other carriers, in certain locations the capacities of the base stations have not been able to keep up with the increased data needs. This had led to speed issues (average quality) and service variability. The implication of our analysis for this case depends on whether the focus is on customers who travel across markets that have 4G LTE service or on the segment that is largely confined to one market. For the former group, Verizon's service quality will have a high mean and low variance—a good situation for the company. For the latter segment, in markets with no congestion, the situation is once again that of high mean and low variance. Now compare Verizon's situation to another provider that does not have as extensive a 4G LTE

(b) a panel version that considers a household's decision to terminate the service each period. The range of the results reported above is a consequence of the differences in elasticities from these alternative specifications.

[33] Although service quality mean and variability are exogenous in our context, we perform these analyses to highlight general implications that are possibly applicable to contexts that are beyond our own where managers can indeed influence quality levels. Moreover, for our specific context, one can construe our implications as being more "long term" in nature. After the test market in the three cities, the company decided to withdraw the service to relaunch at a later date. If the firm now has the capability to boost quality or to influence its variability, these implications would be appropriate.

network coverage as Verizon. Customers of such a provider who sign up for the provider's 4G service are likely to experience mean and variance in quality depending once again on whether they belong to the traveling or to the local segment. If these customers travel extensively in 3G markets, then they would experience lower-than-4G quality with low variation—a situation detrimental to the carrier. Here, the focus should be on the wider rollout of 4G service that increases the average quality of the service for the customer. However, if the customer is confined to a local market with high congestion, then, as in the Verizon case, the company should focus on lowering variability. We recognize that the telecom market is far more complex and does not necessarily have a one-to-one mapping with our VOD business; nevertheless, the general nature of the implications appears to be relevant in that case as well.

6. Conclusion

The positive relationship between customer retention and the average level of service quality has been well established in the literature, but the corresponding link with variability is less clear. Notwithstanding the dominant view that higher variability will lower retention, we document empirically that, in the context of new services, the effect of variability on customer retention might depend on the average service quality. In particular, using model-free evidence, we show the presence of an interaction effect: the marginal reduction in termination with increase in average quality is likely to be higher among customers experiencing low variability. As an extreme outcome, at low quality levels, lowering variability can lead to an increase in termination rates. We show that this effect is not due to the bounded nature of the observed quality being received by households.

We propose a mechanism involving risk aversion and learning that can rationalize this interaction effect. Based on the model and the empirical results, we establish the boundary conditions under which lowering variability can lead to higher termination. From a managerial perspective, we document the relative trade-off between lowering variability and increasing the average quality in terms of their ability to retain customers.

There are several avenues in which the model and empirical analysis can be extended in future research. First, our context reflects two aspects of service quality that have been discussed in the literature (e.g., Parasuraman et al. 1985): service quality is (a) generally inconsistent (i.e., quality of the service varies from customer to customer) and (b) cannot be inventoried (i.e., movies that are not downloaded in a given week because of poor service quality are never available to the household even at a future date). However, it does not reflect the notion that service quality is essentially inseparable (i.e., it is realized as a consequence of interaction between the customer and the service provider) and intangible (i.e., it cannot be measured or quantified precisely). In this regard, our context is similar to common applications such as cell phone service, where customers might be able to objectively infer the quality that they experience and trace it back to the service provider. Nevertheless, even in such contexts (including ours), there are other aspects of service quality such as billing and conflict resolution wherein the intangible and inseparable nature of service quality would be relevant. These, in turn, would render it difficult to understand how customers perceive and evaluate the service as a whole (Zeithaml 1981). Therefore, the aspect of service quality that we consider can be viewed as a component of the composite service quality. If we believe that these other aspects of service quality are orthogonal to the measures that we consider, we can operationalize them by treating the composite service quality as the sum of the objective quality and some uncorrelated, mean zero, random shock from a parametric distribution such as normal. However, one needs to be careful to ensure that the additional parameter that would need to be estimated, namely, the variance of the shock, is identified. On the other hand, if we believe that these shocks are likely to be correlated with the objective measure, we need to consider a more general structure that accounts for such dependence.

Second, in consideration of empirical tractability, we have followed the current literature and specified the learning mechanism in terms of the normal-normal conjugate distribution. Nevertheless, in our model extensions, we account for the bounded nature of signal quality. It appears from that analysis that the key intuition regarding learning deterrence and risk aversion leading to the interaction effect is likely to be invariant to our distributional assumption. At the same time, exploring alternative approaches to accounting for the bounded nature of the signals may be worthwhile from the perspective of having a general model that deals with such data (see Ching et al. 2013 for a discussion of some richer specification of learning models). Finally, one can consider a richer specification of the learning mechanism by incorporating consumer forgetting (Mehta et al. 2004). If the data have additional variation in terms of exogenously different service subscription/renewal frequencies, such as monthly, quarterly, and annual, one can exploit this variation to identify the interaction between learning and forgetting behavior. Managerially, such an analysis might help managers design appropriate contract lengths.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.2105.

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