Marketing Science

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MARKETING SCIENCE
Vol. 29, No. 4, July–August 2010, pp. 690–700
ISSN 0732-2399 | EISSN 1526-548X | 10 | 2904 | 0690

DOI 10.1287/mksc.1090.0550

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This paper documents the existence and magnitude of contiguous word-of-mouth effects of signal quality of a video-on-demand (VOD) service on customer acquisition. We operationalize contiguous word-of-mouth effect based on geographic proximity and use behavioral data to quantify the effect.

The signal quality for this VOD service is exogenously determined, objectively measured, and spatially uncorrelated. Furthermore, it is unobserved to the potential subscriber and is revealed postadoption. For a subscriber, the signal quality translates directly into the number of movies available for viewing, thus representing a part of the overall service quality. The combination of signal quality along with location and neighborhood information for each subscriber and potential subscriber allows us to resolve the typical challenges in measuring causal social network effects.

We find that contiguous word of mouth affects about 8% of the subscribers with respect to their adoption behavior. However, this effect acts as a double-edged sword because it is asymmetric. We find that the effect of negative word of mouth arising from poor signal quality is more than twice as large as the effect of positive word of mouth arising from excellent signal quality. Besides contiguous word of mouth, we find that advertising and the retail environment also play a role in adoption.

Key words: services; service quality; new product adoption; word of mouth; contagion; social networks; high technology; hazard models
History: Received: April 11, 2007; accepted: October 2, 2009; processed by Eitan Muller. Published online in *Articles in Advance* February 16, 2010.

1. Introduction

This paper quantifies the effect of signal quality of a video-on-demand (VOD) service on customer acquisition while accounting for the possible spillover effects arising via word-of-mouth interactions between current customers and potential subscribers. We use a new behavioral data set that contains not only an objective and exogenous measure of signal quality, but also household-level information on factors that could influence spillover effects. Because a subscriber cannot observe the signal quality she will obtain prior to adoption of the service, we investigate whether the signal quality level spills over and influences new customers' activation behavior via (inferred) word-of-mouth interactions with current customers who experience the signal quality postadoption. Because signal quality is one of the major determinants of the performance of the VOD service (we provide these details in a later section), and the word-of-mouth effect about signal quality is inferred, our measure is akin to an *indirect* measure of service quality.

The existence of the indirect effect of service quality has been hypothesized in theory and shown using survey data, but it has not been tested using actual behavioral data (Anderson 1998). Because it is hard to measure service quality and even harder to ascertain whether the current customers actually communicate with potential new customers, the indirect effect of service quality is difficult to quantify.

By contrast, the features of our data enable us to test for the existence of the indirect effect of service quality. The data we use in this paper come from the launch of a new VOD service that requires activation, monthly maintenance, and rental fees. The data span a period from October 2003 to November 2004 and come from three different geographic markets. The service—which we will refer to as DirectMovie[1]—does not require any physical connection to a cable service or to the Internet. The digital (movie) signals are transmitted from terrestrial TV towers using spare television broadcast bandwidth, usually that of a local Public Broadcasting Service station. These digital signals are then decoded by a set-top box (the DirectMovie player, or DMP) that is in turn connected to a regular television. In addition to the decoder, the DMP contains a hard drive allowing it to store up to 100 movie titles. Each week, 10 new movies are broadcast, and the DMP updates its stored movie assortment by adding these 10 movies and dropping the 10 "oldest" movies. The quality of the update is a function of the signal quality of the TV signal received by each DMP. In other words, the noisier the signal that is delivered to the DMP, the fewer the number of movies that get updated. Note that the signal quality only affects whether a movie was downloaded; it does *not* affect the picture quality of the downloaded movie.

One unique feature of the data set is that it records a subscriber's TV signal quality level. This is obtained by the firm from the DMP, which is connected to the firm's main server through the phone line. If a subscriber receives a lower-quality TV signal, she might not have access to all the new movies that would have been available if the updating process had been carried out. Her choice set would then be limited to past movies (that she might already have seen), thus degrading the quality of her experience with the DirectMovie service. Furthermore, the level of signal quality is "exogenous" to the subscriber because she can neither pick a level of quality (as is typical in the services literature) nor can she influence the level of quality received. As we discuss later, this feature of the data is critical for the identification of the contiguous word-of-mouth effect.

Another unique feature of the data set is that it contains the street-level addresses of all subscribers. This allows us to test for the existence and magnitude of spillover (contiguous word-of-mouth) effects. These street-level addresses are converted into distance measures among customers. These interhousehold distances are then used as proxies for social interaction and its effect on customers' adoption behavior (Conley and Topa 2007, Bell and Song 2007, Manchanda et al. 2008). Note that, as described above, the key to identifying the contiguous word-of-mouth effect is that the received signal quality by a household is exogenous to and idiosyncratic for that household. Even if households are located close to one another, they are "endowed" with different levels of signal quality.[2]

Our identification strategy for these effects arises from both the main effect of neighbors *and* the interaction between the number of neighbors and their realized signal quality, while controlling for other geographic and demographic covariates. The main effect can be seen if a higher number of (subscribing) neighbors leads to a higher probability of adoption for a household. The interaction effect implies that more neighbors with higher (lower) signal quality will lead to a higher (lower) probability of adoption. Given the spatially uncorrelated, independent, and exogenous variation in signal quality for each household, this interaction allows us to quantify the indirect effect of signal quality. It is this interaction effect that distinguishes our study from previous efforts to identify word-of-mouth effects (e.g., Bell and Song 2007, Manchanda et al. 2008). In those studies, the identification of the word-of-mouth effect is from the main effect of number of neighbors (who have adopted). In our case, the additional information on whether or not these neighbors receive good or bad signals, and the differential impact of this signal quality on adoption, enhances identification of the word-of-mouth effect.

Thus the mechanism that allows us to obtain a statistically significant interaction is that of information spillover about signal quality in a local neighborhood. We use the label "contiguous word of mouth" for this spillover even though we do not observe intersubscriber communication. This is because potential subscribers do not have any information about their realized service quality prior to adoption (we discuss this in detail in §2.2). However, given our data, other labels—"neighborhood effects" or "geographic contagion"—could also be used. Note that because of the data limitations, we cannot explicitly model word-of-mouth communication that occurs *outside* the geographic bands, e.g., at the workplace or over electronic media. In other words, our identification of the contiguous word-of-mouth effect is subject to our definition of a physical neighborhood.

Specifically, we find that 8% of new subscribers are affected by spillover effects from current subscribers.

[1] Confidentiality reasons keep us from revealing the actual name of the service.

[2] The signal quality received by a specific DMP is a function of the geospatial and line-of-sight characteristics of the subscriber's residence with respect to the nearest terrestrial TV tower. Thus, two subscribers who are neighbors could receive different signal qualities if, for example, one subscriber has a tall tree in her yard but the other does not, or if one subscriber's TV room faces north versus south. Formal tests of signal quality (described in §2.2) also show a lack of spatial correlation in signals.

It is worth noting that the magnitude of this indirect effect of signal quality for DirectMovie is comparable to the magnitude reported by the same households when they are directly surveyed. We find that the effect of negative word of mouth arising from poor signal quality is more than twice as large as the effect of positive word of mouth arising from excellent signal quality.

The rest of this paper is organized as follows. In the next section, we describe the data. In §3 we describe the model. Section 4 contains a discussion of the results. We conclude this paper in §5.

2. Data

In this section, we describe the VOD service, the firm's marketing activity, and its subscriber base. We then explain the role of signal quality and address the identification of the contiguous word-of-mouth effect of service quality in our data.

2.1. Service Description, Subscriber Base, and Marketing Activity

The data come from a large entertainment company that tested a VOD movie rental service, DirectMovie, from October 2003 to November 2004. The service was provided in three test markets—Jacksonville, Florida; Salt Lake City, Utah; and Spokane, Washington—and complete data are available for 3,650 (out of 4,772) subscribers. Our analysis focuses exclusively on these 3,650 subscribers or "adopters" and is therefore conditional on adoption. Jacksonville had the highest penetration ratio (0.2%) and accounted for 45% of total subscribers, followed by Salt Lake City at 44% (Table 1). The data contain the subscription date of the service for *each customer* as well as the numbers of movies rented per week. Each subscriber paid a one-time activation fee of $29.99 and a monthly subscription fee of $7.99. The rental fee was $3.99 for a new release and $2.49 or $1.99 for an old movie.

The primary marketing instrument used by the company to acquire new customers was television advertising. A notable feature of the advertising expenditure was that the temporal pattern of expenditure was virtually identical in all three markets. The advertising was of two types—the majority was conventional spot TV advertising (mean monthly spend $282,000 with a standard deviation of $111,000) and Direct Response TV (DRTV)[3] advertising (mean gross rating points, or GRPs) at 0.83 with a standard deviation of 0.14). Finally, we also have access to a small survey that was administered to a subset of subscribers. The survey data are based on responses from 304 randomly chosen respondents, i.e., about 8% of our estimation sample, across all three markets.

The data include street-level address information of each household in the area. We also collected street-level address information for consumer electronics retailers that were demonstrating and selling subscriptions to DirectMovie and DMPs (Best Buy, Circuit City, and Sound Quality), DVD rental stores, and major shopping malls using each retailer's website and Google Maps. We then use this spatial information to compute the distance (using geographical information system software) between subscribers and consumer electronics retailers, rental shops, and major shopping malls.

We then supplemented these data with demographic information (income, age, cable access, Internet access, education, marital status, number of children, number of teenagers, and race) from the 603 census tracts across the three markets. The demographics for our subscribers show a mean income of $62,297, mean age of 32 years, and mean number of children and teenagers at 0.65 and 0.51, respectively. Our demographics indicate that 15% of the population is 55 years old or older, 19% is single, and 7% is black. Moreover, 19% have cable, 13% have at least a bachelor's degree, and 17% have Internet access. Table 2 provides individual-level data on the time to activate (since launch), (rental) usage, distance between each household and the nearest retail store as well as to the nearest movie rental outlet, and census tract-level (aggregate) demographic information for the census tracts in which their households are located. Because we do not directly observe the demographic information for our customers, for each customer we use the demographic data corresponding to the census tract in which the customer resides.

In summary, our data are a blend of individual-level data (activation, usage, distance to retail and rental stores) supplemented with aggregate demographic data at the census tract level. In addition, we have individual-level survey data from about 8% of the adopter households. Our model therefore is an individual-level model with some controls at the aggregate level (described below).

Table 1 Penetration Ratio by Market

	Jacksonville	Salt Lake City	Spokane
Total population	1,080,925	1,764,891	448,533
Total number of subscribers	2,147	2,061	559
Complete observations	1,608	1,574	469
Penetration ratio (%)	0.20	0.12	0.13

[3] DRTV advertising essentially refers to television programs popularly known as "infomercials." Because this is a medium that is different from TV advertising, we treat these two as different marketing instruments even though both are delivered via television. In addition, the company switched most of its advertising from network TV advertising to DRTV in months 11–14.

Table 2 Descriptive Statistics

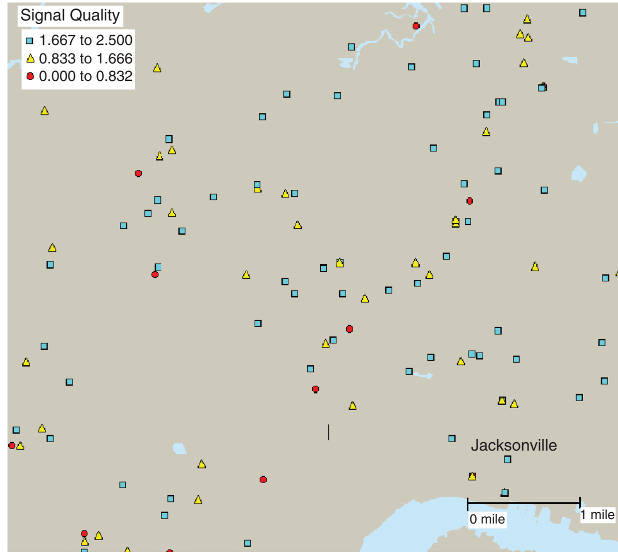
Variables	Obs.	Mean	Std. dev.
Actv_date (days)	3,650	140.2	108.8
Signal quality	3,650	1.66	0.52
Usage (total rentals)	3,650	26.97	25.3
Longitude	3,650	−99.27	15.75
Latitude	3,650	37.01	6.37
Dist_retail (miles)	3,650	3.64	3.11
Dist_rental (miles)	3,650	1.53	1.53
Dist_mall (miles)	3,650	3.80	3.49
Income[a]	3,650	6.37	2.49
Age[a]	3,650	31.76	5.61
Cable[a]	3,650	0.19	0.1
Internet[a]	3,650	0.17	0.03
Education[a]	3,650	0.13	0.06
Single[a]	3,650	0.19	0.06
Child[a]	3,650	0.65	0.27
Teenager[a]	3,650	0.51	0.23
Old[a]	3,650	0.17	0.07
Black[a]	3,650	0.07	0.14

[a]Demographic information is based on the 2002 census tracts: *Income*, mean income level ($10,000); *Age*, mean age of population; *Cable*, the proportion of population with cable; *Internet*, the proportion of population with Internet access; *Education*, the proportion of population with at least a four-year college degree; *Single*, the proportion of population single (never married); *Child*, the number of children (under 13) in a given household; *Teenager*, the number of teenagers (14 to 24) in a given household; *Old*, the proportion of population 55 years or older; *Black*, the proportion of population that is black (non-Hispanic).

2.2. Signal Quality

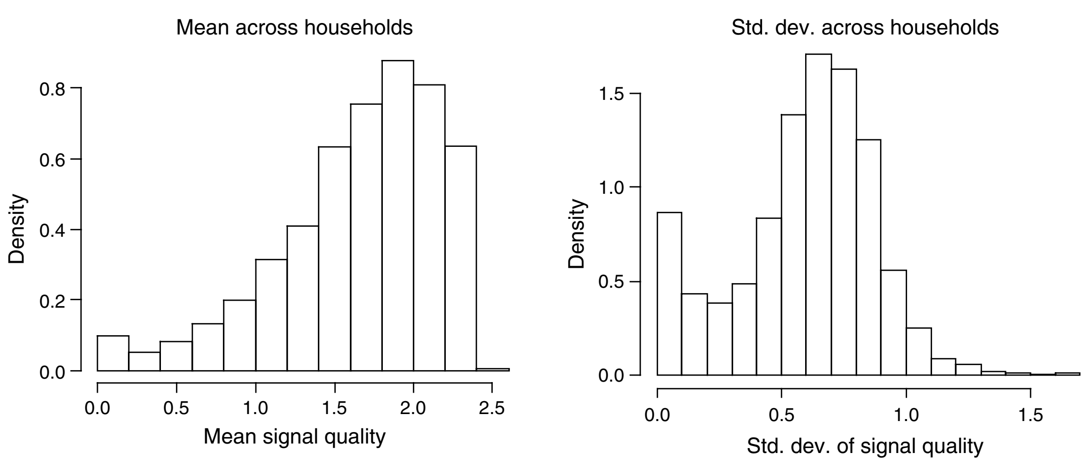
The data include a measure of the signal quality received by the DMP. Recall that this reflects the quality of the terrestrial TV signal received by the DMP. The signal quality has a range from 0 to 2.4 and varies across and within households. Figure 1 shows the means and standard deviations of signal quality across households. In general, the higher the signal quality received by a household, the lower the variation in this quality (the correlation between the mean and standard deviation of signal quality across households is −0.29).

Figure 2 Signal Quality Pattern (Jacksonville)



A unique feature of this signal quality is that there is a lot of variation across geographic locations. Figure 2 shows the household locations and their signal quality levels for the Jacksonville market. As shown in the figure, the signal quality is subscriber specific, not location specific (households right next to each other get different signal qualities). This is also reflected at a "coarser" geographic level. Specifically, the level of variation of signal quality within census tracts (standard deviation of 0.183) is higher than the level of variation of signal quality across census tracts (standard deviation of 0.117). We also computed the correlation between the signal quality for each subscriber and the mean signal quality received by her near neighbors and found the mean correlation to be 0.06. Finally, we carried out a formal test to see if there

Figure 1 Signal Quality Distribution



was any spatial correlation in the signal quality using the test for spatial correlation outlined in Conley and Topa (2002). The intuition behind the test is that it involves the computation of the spatial correlation of the subscribers' signal qualities within a certain distance followed by the comparison with spatial correlation of independently distributed (simulated) signal qualities. Using a uniform kernel bandwidth of 0.05 miles, we find that there is no significant spatial correlation (at the 5% statistical significance level) at distances ranging from 0.1 to 0.5 miles.

As noted earlier, the number of movies that get updated every week is determined by the signal quality received by the DMP that week. As subscribers do not observe signal quality directly, we wanted to ensure that there was a clear relationship between signal quality and the amount of updating. Therefore, using the survey data, we ran a logistic regression with the dependent variable being the response to the question whether all 10 movies were updated every week with their received signal quality (available to us via the database) as the explanatory variable. We find that the coefficient on signal quality was highly significant (t-stat 3.51). This assured us that higher signal quality was indeed predictive of more frequent updating and the subscribers were noting the updating patterns "correctly."

Note also that, as mentioned earlier, signal quality and its relationship with movie assortment is only one dimension of overall service quality for the VOD service. The other components are the billing process; instructions for setting up the system; movie selection; and ease of use of on-screen menus, picture quality, etc. We do not have data on the quality of these dimensions for our estimation sample (with the exception of the satisfaction survey data from 8% of the subscribers). Thus, we are constrained to using only the signal quality measure. We did use the survey data to understand the notion of service quality for the VOD service in more detail. Generally speaking, the survey respondents are quite satisfied on all dimensions other than movie selection (the average score for each dimension is between 9 and 10 on a 10-point scale). However, the satisfaction level on movie selection has the lowest (6.2). We run a regression of overall satisfaction on all these dimensions of service quality as well as on only movie selection. We find that movie selection explains over 50% of the variance in overall satisfaction. This suggests that even though signal quality (the movie assortment) is not a complete measure of overall service quality, it does play a strong role in determining overall satisfaction with the service.

In summary, our modeling approach exploits five aspects of signal quality that we observe in the data. First, signal quality is exogenous as far as the household is concerned. Second, although the firm can raise average signal quality, it cannot target increases in this quality for a household. Third, there is variation in signal quality across and within households over time. Fourth, there is little spatial correlation in signal quality. Finally, a consumer cannot observe signal quality until she subscribes—hence it is very likely that she will base her expectation of her own service quality on her neighbors' service quality. Our hypothesis is that this expectation will most likely be formed as an outcome of contiguous word-of-mouth communication. We discuss this below and describe the covariates of our adoption model.

2.3. Identification of the Contiguous Word-of-Mouth Effect

When the VOD service satisfies current subscribers, it is likely that they would recommend it to other potential subscribers. The survey data suggest that, of the households surveyed, 86% reported that they discussed the service with someone they knew, suggesting that there are likely to be word-of-mouth effects. However, these indirect effects may be confounded with other effects such as those arising from marketing activity. For example, 50% of the survey respondents replied that they heard about the service through TV advertising. Thus we need to control for such confounding factors to isolate the word-of-mouth effect.

A potential manifestation of the above word-of-mouth effect could be spatial correlation in the adoption pattern; i.e., a household living close to one that has previously adopted the service is more likely to also adopt the service. However, an alternative explanation for such a finding could be that adoption patterns are spatially correlated of the presence of some unobserved common geographic characteristics besides observable factors such as income, etc. If this were indeed the case, we would see evidence for adoption in geographic clusters.

We therefore check to see if adoption patterns can be explained by temporal variation (in advertising) and cross-sectional variation (with geographic fixed effects). We estimated a household-level hazard model (with various baseline specifications) with time to adoption as the dependent variable and advertising and 128 geography-specific dummy variables on zip code. For the adoption model with advertising and geography-specific dummies, we find that only six dummy variables are significant. In addition, the Bayesian information criterion (BIC) value does not improve when geographic (dummy) variables are added relative to a model with only advertising effects. Although we recognize that geographic fixed effects specified on a finer spatial definition may better control for unobservables (we discuss how we deal with issue below), our results seem to suggest that individual-level adoption behavior cannot be explained only by common geographic characteristics (at least at the zip code level).

Thus, it is possible that word-of-mouth effects could explain adoption behavior. Previous research (e.g., Richins 1983) has also documented the relationship between product performance and word of mouth, especially for poor product performance. Our approach to test for the presence of these effects is to infer it from two sources. The first source is the presence of other adopters in a potential subscriber's "neighborhood." The second source is the realized service quality received by the adopters in the neighborhood.

Because we do not directly observe that the current subscribers communicate with other potential subscribers, we make two assumptions to capture the role of word of mouth in the adoption (activation) model.

First, we assume that every current and past subscriber in a geographic "band" (circle) around each potential subscriber communicates with the potential subscriber. Because geographically close neighbors are more likely to have interactions than others, using such a band is a common practice in the social interaction literature (see Conley and Topa 2007 for details). We choose the band to be a circle of 0.5-mile radius centered at a potential subscriber's residential location. As discussed earlier, we find that signals are spatially uncorrelated in this band. A half mile is also about a seven- to eight-minute walking distance and a one-minute driving distance, thus facilitating interaction.[4] We count the number of neighbors who have already activated the service within the band. Using this band, we find that at the time of activation, the mean number of existing customers for a potential subscriber is 2.52 (with a standard deviation of 4.22).

Second, we assume that a current subscriber's recommendation to others is a function of her usage-weighted signal up to the previous period. The advantage of using such a formulation is that it captures the dynamics of signal quality within the household and also reflects a potential recommendation based on actual use of the VOD service. The average usage-weighted signal is 1.023 (with a standard deviation of 0.75). For a given potential subscriber, the overall contiguous word-of-mouth effect is a simple average of all the usage-weighted signal quality received by all the current subscribers in her neighborhood. This average allows for both cross-sectional and temporal variation in the quality of signal received in a potential subscriber's neighborhood of potential subscribers. Based on these two assumptions, we can test whether a potential subscriber's decision to subscribe was influenced by the contiguous word of mouth. The necessary condition for the existence of a contiguous word-of-mouth effect is that the time of adoption is influenced by the number of neighbors who have adopted. The sufficient condition is that this adoption time is also a function of the average signal received in the neighborhood.

Another way to think about this is to look at the general identification issues in estimating causal word-of-mouth effects in nonexperimental data (for a detailed discussion of these problems in the marketing context, see Nair et al. 2006, Hartmann et al. 2008). Given that signal quality is exogenous (and not spatially correlated), our sufficient condition helps rule out "endogenous group formation" (the fact that people who locate together may have common tastes) and "correlated unobservables" (factors common to the neighborhood or social network that are unobserved by the researcher) as well as other factors (e.g., sample selection) that could give rise to spurious word-of-mouth effects. The intuition is that if the contiguous word-of-mouth effect is driven by endogenous group formation and/or correlated unobservables, then signal quality should have no effect on an individual subscriber's adoption decision. Our data and approach also help us handle two other issues with regards to identifying contiguous word of mouth. The first of these is "reference group determination"; i.e., the social network must be formed independent of the behavior under consideration. In our case, it is unlikely that households choose to locate in physical neighborhoods in anticipation of their adopting the DirectMovie service. The second is the issue of "simultaneity" or whether a group member influences another group member, or vice versa, does not apply in our case as adoption imposes a temporal ordering (i.e., a household can only be affected by a neighbor after he or she adopts the service).

3. Model and Specification

We first outline our model structure and then describe the model specification.

3.1. Model Structure

For each subscriber, we model the time to adopt using a hazard model with both time-varying and time-invariant covariates.

We model the time to adopt using the discrete time proportional hazard model (PHM) first proposed by Cox (1972). This model consists of two parts: the baseline hazard that captures the intrinsic temporal pattern and the covariate function that captures the influence of covariates on the baseline hazard. We choose the log-logistic (Seetharaman and Chintagunta 2003) as

[4] In a subsequent section, we also show that the model that uses a 0.5-mile radius fits the data better than models that assume a 0.3- and 0.8-mile radius.

the baseline hazard based on two criteria. First, the log-logistic form allows an inverse U shape of the baseline hazard that resembles the overall shape of the empirical hazard of our data. Other baseline hazard choices (e.g., exponential and Erlang-2) are restrictive in that they either show no duration dependence or impose a strictly increasing or decreasing pattern for the baseline hazard. Second, the model assuming a log-logistic baseline hazard fits the data better than some competing specifications (details provided in §4.1).

The baseline hazard ($h(t, X_t)$) for activation is defined as the probability that a potential subscriber subscribes to the service at time t, given she has not activated the service until that time:

$$h(t, X_t) = h(t) \cdot e^{X_t\beta} = \frac{f(t, X_t)}{1 - F(t, X_t)} = \frac{f(t, X_t)}{S(t, X_t)}. \quad (1)$$

Here, $f(t, X_t)$ denotes for the subscriber's probability of activating the service at time t, and $S(t, X_t)$ (called the survival function) is for the probability that the subscriber has not yet activated the service. The covariates X_t (both time varying and invariant) scale the baseline hazard up or down by multiplying the baseline hazard via $e^{X_t\beta}$ term. The closed-form expressions for the survivor function and probability density function, respectively, are

$$S(t, X_t) = e^{-\sum_{u=1}^{t} e^{X_u\beta} \int_{u-1}^{u} h(w)\, dw}, \quad (2)$$

$$\Pr(t, X_t) = 1 - e^{-e^{X_t\beta} \int_{t-1}^{t} h(u)\, du}, \quad (3)$$

where the hazard function has a log-logistic form

$$h(t) = \frac{\gamma\alpha(\gamma t)^{\alpha-1}}{1 + (\gamma t)^{\alpha}}. \quad (4)$$

Given this probability density function and survivor function, we construct the likelihood function for a household i as

$$L_i = \prod_{v=1}^{T} (\Pr(v, X_{iv})^{\delta_{iv}} [1 - \Pr(v, X_{iv})]^{1-\delta_{iv}})^{\chi_{iv}}, \quad (5)$$

where δ_{iv} is an indicator variable that takes the value one if the subscriber i activates the service at time v and zero otherwise. χ_{iv} takes the value one if the subscriber i has not activated the service in the past and zero otherwise.

To account for the unobserved heterogeneity across consumers in the baseline hazard, and subscribers' sensitivities to covariates, we use a mass point distribution for these parameters and then estimate the supports and probability masses for the distribution from the data (Heckman and Singer 1984, Kamakura and Russell 1989). The corresponding likelihood function can be written as follows:

$$L = \prod_{i=1}^{N} \left(\sum_{s=1}^{S} L_{i|s} \pi_s \right), \quad (6)$$

where N denotes the total number of subscribers, S is the total number of mass points, $L_{i|s}$ is the likelihood function of a household given that it is associated with mass point s, and π_s refers to the probability mass associated with mass point or segment s. We use maximum likelihood methods for estimation.

3.2. Model Specification

We now describe the specification for the model (a detailed list of all the explanatory variables can be found in Table 2). As described earlier, activation of the service could be a function of marketing activity by the firm, word-of-mouth effects, or household demographics. For marketing activity, we include the aggregate level of conventional TV and DRTV advertising as time varying covariates. For contiguous word of mouth, we include the main effect of number of neighbors ($Neighbor_{i,t}$) and the interaction effect between number of neighbors and the square root of neighbors' usage-weighted signal quality ($qual_{i,t}$). A significant coefficient for the latter term represents the sufficient condition (as described earlier) for the identification of the contiguous word-of-mouth effect.[5]

$$X_t\beta = \mu \cdot Neighbor_{i,t} + \rho \cdot Neighbor_{i,t} \cdot \sqrt{qual_{i,t}} + \sum_{j=1}^{J} \tau_j \cdot demo_{i,j}. \quad (7)$$

The use of the square root function has the attractive properties that it allows for an overall nonlinear (with diminishing returns) contiguous word-of-mouth effect.[6] Note that the parameters μ and ρ reflect both the amount of interaction as well as the effectiveness of these interactions. In other words, we cannot distinguish between a subset of neighbors having more effective interactions and all the neighbors having less effective interactions.

For demographics ($demo_{i,j}$), we use the distance to the nearest (electronics) retail store, the distance to the nearest DVD rental store, the distance to the nearest mall (using Google Local, we found 24 malls around Jacksonville, 21 around Salt Lake City, and 11 around Spokane), and census tract-level demographics. The distance to the nearest (electronics) retail store would represent the degree of access to the retail shop where consumers can see the demonstration of the service

[5] Note the Equation (7) does not contain the main effect of service quality *for that subscriber*. This is because the realized service quality for a subscriber is unobservable to that subscriber until she adopts the service.

[6] We also compared the fit of a model with a linear signal quality formulation with the fit using the square root formulation and found that the latter fit the data better on statistical fit criteria and predictive ability both in and out of sample.

and can activate the service. The distance to the nearest rental shop and to the nearest shopping mall is used to model other shopping, renting, and movie-viewing options. Because census tract demographics may not capture all differences across the three markets, we include market-specific fixed effects.

4. Results and Discussion

Table 3 shows the estimation results. As noted previously, we use a mass point or latent segment approach to account for household heterogeneity. We find significant heterogeneity in the estimated baseline hazard and the effect of covariates. Using the BIC fit criterion, we choose the three-segment solution. Each column shows the segment-specific parameters associated with the baseline hazard and time covariates. The parameters for the (pooled) demographic variables are listed in the last column.

We classify each subscriber into one of three segments using the maximum posterior probability rule (Kamakura and Russell 1989). The demographics of these three segments are described in Table 4. Segment 1, with smallest mass (8%), has the lowest mean annual income ($62,469) and highest black ratio (9.1%). In contrast, segment 2, with 52% of the mass, has the highest income ($64,606) and lowest black ratio (6.9%). The demographics for segment 3, with the mass at 40%, are between those of segments 1 and 2.

We find that the estimated activation baseline hazard is different across the segments. The activation hazard associated with segment 1 is increasing over time, and segment 2 is decreasing in a convex fashion over time. The baseline hazard associated with segment 3 has an inverse U shape. The magnitude of the hazard for segment 3 is also slightly higher than for the other segments.

Table 3 Parameter Estimates

	Seg1		Seg2		Seg3		Demo	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE
log(Alpha)	**3.274**	0.216	**−1.449**	0.24	**1.162**	0.115		
log(Gamma)	**−2.501**	0.033	**−4.705**	1.596	**−1.772**	0.093		
Neighbor	**−0.894**	0.368	0.137	0.099	−0.085	0.088		
Nei ∗ sqrt (qual)	**0.727**	0.304	−0.09	0.084	0.104	0.075		
Ad ($100,000)	**2.743**	0.989	**0.612**	0.066	0.045	0.048		
DRTV (1,000 GRP)	1.715	1.057	**6.684**	0.423	**2.794**	0.485		
Dist_retail (mile)							**−0.018**	0.008
Dist_mall (mile)							0.008	0.007
Dist_rental (mile)							0.011	0.016
Income ($10,000)							**0.05**	0.009
Single (%)							−0.001	0.471
Child (no. per HH)							0.165	0.137
Old (55+, %)							0.486	0.455
Black (%)							−0.065	0.166
SLC							−0.07	0.063
SPK							−0.118	0.07
Proportion	0.08		0.52		0.40			

Notes. Parameters in bold are statistically significant at $p < 0.05$ level. SE, standard error.

Table 4 Demographics by Segment

Variables	Seg1	Seg2	Seg3
Jacksonville (JSV)	0.38	0.47	0.45
Salt Lake City (SLC)	0.47	0.41	0.45
Spokane (SPK)	0.10	0.13	0.13
Dist_retail (mile)	3.70	3.65	3.60
Dist_rental (mile)	1.47	1.57	1.48
Dist_mall (mile)	3.55	3.90	3.70
Signal quality	1.710	1.654	1.594
Income ($)	62,469	64,605	62,510
Single (%)	0.20	0.19	0.20
Child (no. per HH)	0.65	0.64	0.66
Old (55+, %)	0.17	0.17	0.17
Black ratio (%)	0.09	0.07	0.07
No. HH in segment	336	2,005	1,309

We now turn to the effect of the covariates on the hazard. As shown in Table 3, the contiguous word-of-mouth effect as represented by the main effect, and the interaction is significant only for segment 1 (with 8% of the mass). In other words, a potential subscriber's adoption behavior in this segment is significantly affected by the number of neighbors who are adopters and the average usage-weighted signal quality (realized by these adopters).

We now examine this effect in more detail. As shown in Table 3, the main effect of neighbors is negative and the interaction effect with the square root of the signal quality is positive. Thus, adoption by an additional neighbor does not always lead to an increase in the adoption probability of a focal household. The determination of whether the adoption by a neighbor decreases or increases the probability of adoption for the focal household is based on the usage-weighted signal quality received by the adopter. Specifically, for usage-weighted signal levels that are higher than 1.51 (on a scale from 0 to 2.4), the adoption probability for the focal household goes up although it goes down for all usage-weighted signal levels below this number. Interestingly enough, this effect is also asymmetric below this "break-even" level of signal quality. This can be illustrated by looking at the extremes—when the signal quality is at its lowest level (0), the hazard rate drops by 59%, but when it is at its maximum (2.4), the hazard rate only goes up by 26%. For the firm, it may also be helpful to quantify the change in hazard relative to the average signal quality delivered (as the firm has the ability to change the average quality). Thus, a 50% increase in the signal quality relative to the mean leads to an increase in hazard of 15%, whereas a 50% decrease in the signal quality leads to a 31% decrease in the hazard rate.

These results are consistent with the theory that predicts that contiguous word of mouth would have a positive effect on others' behaviors if the customers' satisfaction levels (based on product quality) are above a certain threshold and have a larger negative effect when consumers' satisfaction levels are below that same threshold. The presence of the larger negative effect has been variously attributed to expectations disconfirmation (Oliver 1980), proclivity (Anderson 1998), prospect theory (Kahneman and Tversky 1979), higher diagnosticity of negative information (Herr et al. 1991), and the more contagious nature of negative information—especially when both positive and negative information are present (Rozin and Ryzman 2001). With our data, we cannot test which mechanism is operating here—thus, our findings must be seen as providing a confirmation of the effect in a field setting.

Advertising also helps in customer acquisition. A $10,000 increase in network TV advertising spending and a 10-point increase in GRPs delivered via DRTV, increases a potential subscriber's monthly adoption probability by 0% and 6.1%, 27.5% and 2.79%, and 6.7% and 0% for segments 1, 2, and 3, respectively. Although about 60% of consumers activated the service via the phone or the Internet, activation behavior is affected significantly by distance to the nearest consumer electronics retailer. When a subscriber lives one mile farther from the nearest retailer, the monthly activation rate decreases by 1.8%. Consumers who have easier access to the retailer might activate the service with lower uncertainty by seeing the display of the service in the retailer. In terms of demographics, we find that households in census tracts with higher mean annual income are more likely to adopt. For every additional $10,000 in a household's mean annual income, the adoption probability increases by 5%. Finally, we do not find market-specific fixed effects on activation because both the Salt Lake City and Spokane fixed effects are not significantly different from zero (Table 3).

In summary, we find that contiguous word of mouth affects about 8% of the subscribers with respect to their activation behavior.[7] Interestingly, when consumers were asked in the survey, "Before you signed up for the service, where did you see or hear about the service?", 8% of them replied in the affirmative. We also carried a simple analysis where we plotted the adoption timing of all consumers in the sample when contiguous word-of-mouth effect is based on the highest possible signal quality as opposed to the lowest possible signal quality. We find that the adoption time is reduced by about 55 days on average (or about 16%). Note that this number represents an upper bound of the indirect effect. Finally, the contiguous word-of-mouth effect acts as a double-edged sword because it is asymmetric in nature with the negative effect at the lowest level of signal quality being more than twice the positive effect at the highest level of quality.

[7] Although it may seem that the size of the segment influenced by contiguous word of mouth is "small" relative to the other segments, this may be because the duration of our data is limited—we only have 13 months of data postlaunch.

Table 5 Comparison of Various Baseline Hazard Specifications

	Log-logistic	Exponential	Erlang-2
LL	−8,714.1	−8,776.2	−8,777.7
BIC	17,722.9	17,817.6	17,820.7
In-sample fit, MAPE	0.075	0.188	0.175
Out-of-sample fit, MAPE	0.28	0.543	0.818

Note. LL, log-likelihood; MAPE, mean absolute percentage error.

Figure 3(a) In-Sample Model Fit

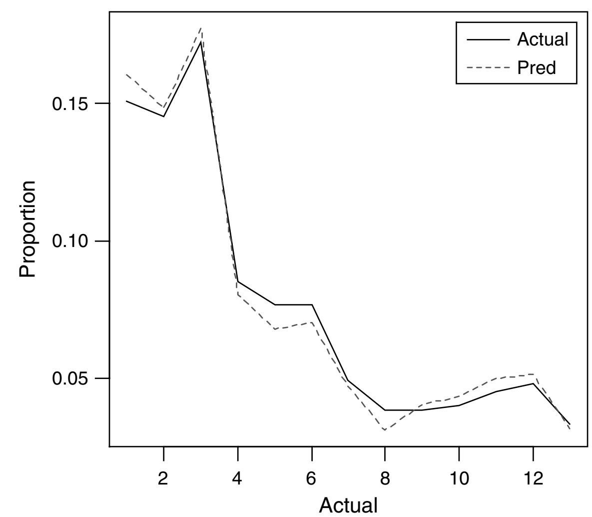
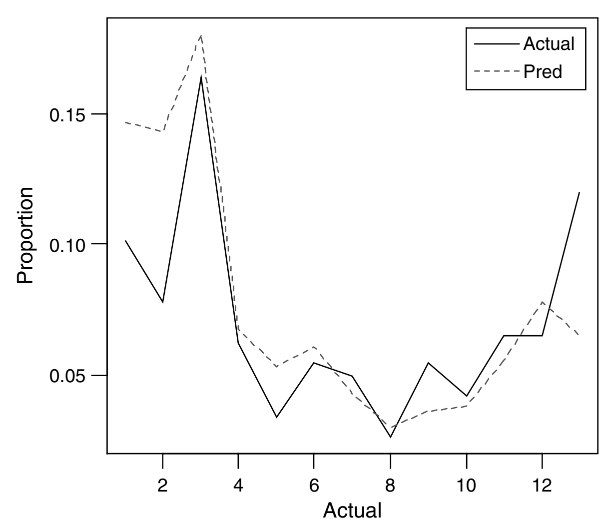


Figure 3(b) Out-of-Sample Model Fit



4.1. Alternative Specifications

We also investigated alternative specifications with different specifications for the baseline hazard and the choice of the band distance.

For the baseline hazard, we compared three different specifications—the log-logistic, the exponential, and the Erlang-2. The results of the comparison are in Table 5. From this table, we see that the log-logistic has the best fit and does the best on prediction. Note that for the out-of-sample fit, we first reestimated the model holding out 385 customers (about 10% of the sample). We then used these estimates to predict the adoption probabilities of these "hold-out" customers. We therefore chose the log-logistic baseline hazard. Figures 3(a) and 3(b) illustrate the in- and out-of-sample predictions over time (using the model estimates).

We also explored the fit of our model as a function of the choice of the geographic band for interactions in our model. We looked at the BIC for the range of 0.3 miles to 0.8 miles (in 0.1-mile increments). We found the BIC to be 17,722.9 for 0.5 miles, 17,726.3 for 0.3 miles, and 17,733.7 for 0.8 miles. Hence 0.5 miles appears to be the appropriate choice based on model fit.

5. Conclusion

This paper contributes to the service marketing and social networking literature by showing the existence and quantifying the effect of indirect effects of signal quality of a VOD service on new customer acquisition using behavioral data. We use a unique data set describing the launch of a new high-tech entertainment product (a video-on-demand–type service). For this technology, signal quality (a component of overall service quality) is exogenously determined, objectively measured, and spatially uncorrelated. This information is coupled with location and neighborhood information for each subscriber.

These features allow us to resolve the typical challenges of determining causal social network effect. Our identification strategy for the contiguous word-of-mouth effect is based on the main effect of neighbors *and* the interaction between the number of neighbors and their realized signal quality. The interaction term implies that if a focal household has more neighbors with higher (lower) signal quality, it will lead to a higher (lower) probability of adoption. Specifically, the use of this interaction term allows us to control for correlated unobservables and endogenous group formation. We also control for other factors such as advertising, demographics, and proximity to retail to isolate the contiguous word-of-mouth effect.

We find that contiguous word of mouth affects about 8% of the subscribers with respect to their activation behavior. However, this effect acts as a double-edged sword because it is asymmetric in nature with the negative effect at the lowest level of signal quality being more than twice the positive effect at the highest level of quality.

Our research has some limitations. First, the nature of the service and our data make it hard to identify ex-ante the actual potential population for this service. Thus, we cannot quantify the effects of the change in service quality on individual nonsubscribers. This may also result in an upward bias in some of our estimates. However, it should be noted that this is a general problem for new products when the target population is unrestricted.[8] Also, as mentioned earlier, the lack of data precludes us from examining the other dimensions of service quality and their effect on adoption behavior via the contiguous word-of-mouth effect. The lack of data also precludes us from looking at heterogeneity in matching preferences because we do not observe all the movie titles stored in the DMP for all households. Finally, whereas we have supplemented our data with demographics at the census tract level, we do not have detailed demographic information at the household level. We hope that future research will be able to address these limitations.

Acknowledgments

The authors thank Hongsuk Yang, seminar participants at the Winter AMA Educators' Conference 2008, Marketing Science Institute/USC 2007 Conference, Productive Development and Management Association Conference 2006, University of Chicago, The Wharton School, INSEAD, New York University, University of Toronto, University of Missouri-Columbia, Korea University, Rutgers Business School, the London Business School 2006 Summer Camp, and the 2006 Marketing Science Conference in Pittsburgh for valuable feedback. The authors thank an anonymous firm for providing the data, and Sridhar Narayanan, Hongju Liu, and Neal Rich for help with the data. The authors acknowledge research support from the Kilts Center for Marketing at the University of Chicago.

References

Anderson, E. W. 1998. Customer satisfaction and word of mouth. *J. Service Res.* **1**(1) 5–17.

Bell, D. R., S. Song. 2007. Neighborhood effects and trial on the Internet: Evidence from online grocery retailing. *Quant. Marketing Econom.* **5**(4) 361–400.

[8] To investigate this in more detail, we carried out an analysis (not reported here) to examine the effect of signal quality on the number of acquired subscribers in a census tract (controlling for the total number of households in each tract). Our results indicate that signal quality has a positive and significant effect, suggesting that our results may be robust to the inclusion on nonadopters.

Conley, T. G., G. Topa. 2002. Socio-economic distance and spatial patterns in unemployment. *J. Appl. Econometrics* **17**(4) 303–327.

Conley, T. G., G. Topa. 2007. Estimating dynamic local interactions models. *J. Econometrics* **140**(1) 282–303.

Cox, D. R. 1972. Regression models and life-tables. *J. Roy. Statist. Soc. Ser. B* **34**(2) 187–220.

Hartmann, W. R., P. Manchanda, H. Nair, M. Bothner, P. Dodds, D. Godes, K. Hosanagar, C. Tucker. 2008. Modeling social interactions: Identification, empirical methods and policy implications. *Marketing Lett.* **19**(3–4) 287–304.

Heckman, J., B. Singer. 1984. A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica* **52**(2) 271–320.

Herr, P. M., F. R. Kardes, J. Kim. 1991. Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. *J. Consumer Res.* **17**(4) 454–462.

Kahneman, D., A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* **47**(2) 263–292.

Kamakura, W. A., G. J. Russell. 1989. A probabilistic choice model for market segmentation and elasticity structure. *J. Marketing Res.* **26**(November) 379–390.

Manchanda, P., Y. Xie, N. Youn. 2008. The role of targeted communication and contagion in product adoption. *Marketing Sci.* **27**(6) 950–961.

Nair, H. S., P. Manchanda, T. Bhatia. 2010. Asymmetric social interactions in physician prescription behavior: The role of opinion leaders. *J. Marketing Res.* Forthcoming.

Oliver, R. L. 1980. A cognitive model of the antecedents and consequences of satisfaction decisions. *J. Marketing Res.* **17**(4) 460–469.

Richins, M. L. 1983. Negative word of mouth by dissatisfied consumers: A pilot study. *J. Marketing* **47**(Winter) 68–78.

Rozin, P., E. B. Royzman. 2001. Negativity bias, negativity dominance, and contagion. *Personality Soc. Psych. Rev.* **5**(4) 296–320.

Seetharaman, P. B., P. K. Chintagunta. 2003. The proportional hazard model for purchase timing: A comparison of alternative specifications. *J. Bus. Econom. Statist.* **21**(3) 368–382.