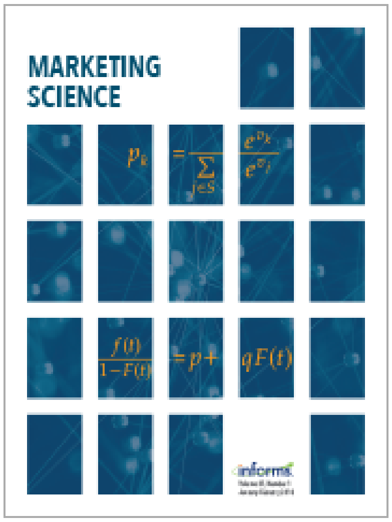


Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Complementarities and the Demand for Home Broadband Internet Services

Hongju Liu, Pradeep K. Chintagunta, Ting Zhu,

MARKETING SCIENCE
Vol. 29, No. 4, July–August 2010, pp. 701–720
ISSN 0732-2399 | EISSN 1526-548X | 10 | 2904 | 0701

DOI 10.1287/mksc.1090.0551

Complementarities and the Demand for Home Broadband Internet Services

Hongju Liu
School of Business, University of Connecticut, Connecticut 06269, hliu@business.uconn.edu

Pradeep K. Chintagunta, Ting Zhu
Booth School of Business, University of Chicago, Chicago, Illinois 60637
{pradeep.chintagunta@chicagobooth.edu, tzhu@chicagobooth.edu}

Before the deregulation of digital subscriber line (DSL) services by the Federal Communications Commission (FCC) in 2005, phone companies were required to share their DSL bandwidth with independent DSL providers. Despite the large number of independent providers that entered the market, phone companies accounted for 95.3% of all DSL subscribers in 2005. A common explanation for this is based on supply-side factors such as the costs faced by these providers to lease phone lines from phone companies, as well as the price discounts offered by phone companies. In this paper, we look for a demand-side explanation for this market outcome. Analyzing consumer choices in the broadband category alone would lead us to the conclusion that consumers have a much higher preference for their local phone providers—a finding at odds with service awards received by independent DSL providers. Thus we look for a demand-side explanation that is based on the demand not just for broadband services but also for related services such as cable TV and local phone. We find evidence of strong complementarities between the consumption of broadband and of those related categories. The main source of such complementarities, in our data, is the benefits to consumers from having a single provider for multiple services. We then carry out counterfactual experiments assuming that there are no changes in the regular prices of the various services. Our results indicate that the share of phone companies in the broadband market would have been 43% smaller without complementarities stemming from such a single-provider effect, whereas shutting off the state dependence effects would have reduced their share by 30%, and shutting off the effects of price discounts on the DSL + local phone bundle would have resulted in their share declining by 21%.

Key words: complementarities; product bundle; broadband
History: Received: December 2, 2008; accepted: October 10, 2009; processed by Michel Wedel. Published online in *Articles in Advance* February 16, 2010.

1. Introduction

The market for home broadband Internet services is dominated by two competing technologies: the cable modem based on cable companies' infrastructure and the digital subscriber line (DSL) based on phone companies' networks. Cable modem and DSL were under asymmetric regulation (see, e.g., Crandall et al. 2002) until August 2005. Cable companies were generally not required to open their infrastructure to other companies, whereas phone companies had to share their bandwidth with competitors at attractive prices. According to the Federal Communications Commission (FCC 2006), there were 818 asymmetric DSL (ADSL) providers and 268 symmetric DSL (SDSL) providers as of December 2005.[1] On average, there were 27 ADSL providers and 13 SDSL providers in each state. Most of these providers leased lines from phone companies to provide their DSL services. Such Internet service providers (ISPs) are often called independent or third-party ISPs (e.g., Covad, EarthLink, Speakeasy). It was the hope of the FCC that by sharing the broadband network of phone companies, independent ISPs would thrive and in turn facilitate faster adoption of broadband. However, independent ISPs struggled. Among the 19.9 million DSL subscribers at the end of 2005,[2] only 4.7% were served by independent providers.

A number of factors might have contributed to the limited success of independent ISPs. For example, leasing lines from phone companies may have put them at a cost disadvantage.[3] Also, independent DSL

[1] One of the explanations for the large increase in the number of DSL providers is that firms enter the market at a rate faster than demand expands if early entry deters future competitors' entry in developing industries (Shen and Villas-Boas 2009).

[2] This includes both residential (17.5 million) and business (2.4 million) customers.

[3] See, for example, *Red Herring* (2001) and Reardon (2005).

providers had to rely on phone companies for installation and maintenance, which could have caused service delays and complaints.[4] Indeed, a vast majority of papers (e.g., Kalakota et al. 2002, Hausman 2002) and discussions (e.g., Crandall 2005) focus on these factors as key drivers of the limited penetration by independent ISPs. Given the large number of third-party DSL providers with some offering award-winning service quality,[5] the 95.3% market share of DSL subscribers held by phone companies is still surprising. In this paper, we ask the following question: Based on an analysis of consumer demand for broadband and other related household services, can we identify some additional explanations for the overwhelming success of phone companies relative to independent ISPs in providing DSL services? In other words, can we identify factors that may favor the DSL services offered by phone companies, leading to their higher market shares?

There could be several reasons why a consumer or a household may prefer to obtain their broadband services from their local phone or cable operators. First, and most obviously, cable companies and phone companies are monopolists in cable TV services and local phone services, respectively.[6] Therefore both types of companies can provide services in multiple product categories,[7] and price discounts are usually offered if consumers subscribe to more than one service from the same company. Such price discounts may induce consumers to purchase DSL services in a bundle with local phone services. Second, most third-party providers had to rely on the infrastructure of cable companies and phone companies, who had been providing cable TV, local phone, and broadband services before third-party providers could enter a market. A first-mover advantage in combination with state dependence effects can make it harder for third-party providers to compete. Third, when consumers decide on whether to adopt broadband Internet access, they may take into account the effects of other product categories on their broadband consumption. In particular, there are two types of such cross-category effects.

There could be cross-category complementarity or substitution effects that may or may not favor either independent providers or the incumbent cable and phone companies. For example, broadband Internet access may help consumers obtain more information about TV programs. Such intrinsic synergies between product categories introduce one source of complementarity. Similarly, broadband and the other categories can also be substitutes. High-speed Internet access may provide a competing source for news and entertainment to cable TV, and likewise the Internet may create alternative ways of communication to a phone, such as e-mails, online chat tools, etc. Although the presence of complementarity and substitution effects will likely influence the demand for broadband services, note that in both the cases mentioned, we would not expect competitive disadvantages for third-party ISPs relative to local phone and cable companies because these effects are at the category level.

In addition to the intrinsic complementarity and substitutability across categories, if two services are provided by the same company, consumers may value the benefits of paying a single bill and dealing with a single provider. This single-provider effect may induce "complementarities" between cable modem and cable TV and between DSL and local phone. Under this type of complementarity effect, consumers may favor the DSL services offered by phone companies because the complementarity exists at the firm–product level. On the other hand, if two services share the same provider, they might go out at the same time. This concern may induce consumers to favor multiple providers for different services as an "insurance policy."

Therefore, when trying to identify the specific demand-side factors for the success of phone companies' DSL services, merely investigating choices of households within the broadband category (say, when prices of the various DSL services are comparable) could lead us to the conclusion that households have a much stronger preference for DSL provision from phone companies—a conclusion that would have been at odds with the accolades received by independent providers for their services. Thus our demand model and analysis need to control for price effects (to deal with the effects of price discounts), for state dependence effects, and for possible complementarity and substitutability across service categories such as local phone, cable TV, and broadband to the extent that these categories are related to broadband consumption via the cross-category effects. Furthermore, we need to be able to identify the main sources of such complementarities or substitution effects if they exist in the data (the single-provider effect or cross-category effects, or both).

[4] See, for example, Fordahl (2001) and Little and Crockett (2001).

[5] For example, EarthLink received a *PC Magazine* Reader's Choice award for high-speed Internet services in 2003, and Speakeasy received *PC Magazine* Reader's Choice award for DSL services in 2006.

[6] Voice over Internet Protocol (VoIP) technology has made it possible for Internet providers to offer phone services. However, it was still a new and emerging marketplace in 2005. In particular, 2.8% of Forrester survey respondents had VoIP services in our data. We removed such observations from our sample.

[7] Both cable companies and phone companies now provide a triple-play package that includes TV, phone, and broadband. This postdates our data and thus we focus on two-product bundles only.

A major difficulty when trying to measure complementarity or substitutability in a cross-category demand model is that of separating out these effects from pure preference correlation, i.e., when consumers who have a high preference for cable TV also have a high preference for broadband services. In other words, the mere observation that two products (e.g., local phone and DSL) are often consumed together does not constitute evidence of complementarity by itself. It could happen because people who like one product also like the other. Under this positive correlation in consumer preferences, people would also purchase the two products together. To separately identify complementarity or substitutability from preference correlation, we exploit the panel structure of our data set and the rich exclusion restrictions in the markets for home broadband and its related products.

In particular, using panel data on households' subscription decisions on cable TV, local phone, and broadband Internet access (i.e., cable modem and DSL), we estimate a multicategory version of the mixed logit model (McFadden and Train 2000) to study household preferences, complementarity, and price effects across these categories. Choices in the local phone and cable TV categories are restricted to whether consumers subscribe to these services from their market-specific provider. For broadband Internet access, consumers choose not only between the no-purchase, cable modem, and DSL options, but they also choose between independent service providers and the incumbent phone or cable companies for the corresponding service. Because consumers add and drop services over time, they are assumed to make joint decisions on whether to subscribe to each of the three services in each time period. We assume that consumers make these subscription decisions to maximize their utility in each time period.

We allow for consumers to vary in their preferences for different categories and different brands—i.e., for unobserved consumer heterogeneity. We account for complementarity and substitution effects across categories, both at the category level and at the provider level, the latter to accommodate the single-provider effect. Two types of state dependence are also accounted for (1) consumers' tendency to remain with their current subscription decisions, and (2) consumers' tendency to keep the same service providers over time giving current providers an advantage in providing additional services.

Whereas our model follows a rich and growing literature on cross-category purchase decisions (e.g., Manchanda et al. 1999, Seetharaman et al. 1999, Russell and Petersen 2000, Chung and Rao 2003, Wedel and Zhang 2004, Seetharaman et al. 2005, Song and Chintagunta 2006, Gentzkow 2007), in this study we focus on pursuing the source of complementarities or substitution effects in addition to disentangling them from preference correlations and price effects, and furthermore, we explore the factor(s) that may have contributed to the competitive advantages of phone companies over independent DSL providers in the broadband market.

Although our model is similar to that in Gentzkow (2007), our formulation differs along the following key aspects: (1) our model formulation allows for two kinds of complementarity effects (the standard complementarity at the category level investigated by Gentzkow as well as the single-provider effect); (2) we are able to incorporate state dependence in the model with the state dependence coming from the overall carryover in the choice vector of services from one period to the next, as well as state dependence from the carryover of a specific provider from one period to the next; and (3) we are able to allow for a richer pattern of heterogeneity across households. These various model enhancements—critical to our research question—are facilitated by the richer panel structure of the data where households also come from markets that exhibit price variation in the services.

We find evidence of strong complementarities between consumption of cable TV and cable modem, and between consumption of local phone and DSL, after controlling for price effects and preference correlations. The main source of such complementarities is the benefits to households in having a single provider for multiple services. In the absence of such benefits, the market share of phone companies' DSL services in the broadband market would have reduced by 43%. Compared with the single-provider effect, price discounts and state dependence play a less important role on households' decisions to purchase product bundles. If phone companies gave no discount on the local phone + DSL bundle, the market share for their DSL services would have dropped by 21%; without any state dependence, phone companies would have obtained a 30% lower share in the broadband market.

In August 2005, the FCC ruled that phone companies were no longer required to share their DSL network with independent providers. To understand the impact of this policy change, we carried out a counterfactual experiment in which we assume that all independent DSL providers would exit the market. In addition we had to assume the quality and availability of all other services remain the same. Because we do not have a pricing model, we calculated the compensating variation at the observed prices in 2005. We find that the welfare loss would be a moderate \$493 million per year on a total revenue base of \$15 billion for the broadband category. Furthermore, if DSL prices from phone companies rose by 10%, the loss in welfare would be \$1 billion.

After describing the data in the next section, we discuss the identification issue with some reduced-form analysis. We then continue with our model, results, and conclusion.

2. Data

In this paper we study households' adoption decisions in three categories: cable TV, local phone, and broadband Internet access. In the broadband category, households can choose between two competing technologies, cable modem and DSL. Cable modem services are offered by cable companies or third-party providers in certain markets, whereas DSL services are offered by the incumbent phone companies as well as by some third-party providers.

The broadband market started to grow rapidly in the early 2000s. According to the FCC, there were only 3.2 million residential high-speed lines in 2000; the number had reached 50.3 million in 2006. Cable modem and DSL are the two dominant technologies in the broadband market. Together they accounted for 95.5% of the broadband connections in 2006. Other types of broadband connections include satellite, fixed wireless, power lines, etc.

Our panel data come from combining the Consumer Technographics surveys in 2004–2006 from Forrester Research. The data reflect market information from 2003–2005, prior to the change in regulation. The survey goes out to about 60,000 households in the United States and Canada each year with some overlap in respondents. From these data we were able to obtain a panel of 2,590 households in the United States who participate in all three years. We have detailed information on household demographics and their subscription to cable TV, local phone, and high-speed Internet. We also obtain characteristics of cable TV from the *Television and Cable Factbook 2006* by Warren Communications News.

Table 1 summarizes households' subscription decisions. The number of subscribers to broadband was on the rise, whereas the number of subscribers to local phone dropped significantly in 2005. Cable TV seemed to be losing customers as well but at a slower rate than local phone. Specifically, over the three-year period, the number of cable subscribers in our panel declined at an annual rate of 2.6%, whereas the number of local phone subscribers declined at a rate of 3.7% a year. Broadband subscribers—both cable modem and DSL subscribers in Table 1—increased at an annual rate of 59%, consistent with the national growth rates. In Figure 1, we plot the share of independent DSL providers among all DSL subscribers in the top 25 markets.[8] Independent providers did not achieve a dominant position in any of these markets.

[8] In this study the market is defined as the designated market area (DMA).

Table 1 Summary of Household Subscription Decisions

Subscribe to	2004	2005	2006
None	169	141	218
In-house cable modem (CM)	1	2	2
In-house DSL	0	0	5
Third-party CM	0	0	0
Third-party DSL	2	0	2
Local	773	757	660
Local + in-house CM	9	20	15
Local + in-house DSL	35	93	161
Local + third-party CM	1	5	3
Local + third-party DSL	7	11	14
Cable	218	203	261
Cable + in-house CM	26	45	78
Cable + in-house DSL	0	0	6
Cable + third-party CM	0	0	0
Cable + third-party DSL	0	1	0
Cable + local	1,143	952	728
Cable + local + in-house CM	146	220	236
Cable + local + in-house DSL	42	119	174
Cable + local + third-party CM	3	5	5
Cable + local + third-party DSL	15	16	22
Total	2,590	2,590	2,590
Cable TV subscribers	1,593	1,561	1,510
Local phone subscribers	2,174	2,198	2,018
Broadband subscribers	287	537	723

Households reported the monthly prices they paid for each service. We use the average reported prices in each market as the prices faced by the households in that market to smooth out the effects of specific services that an individual household may subscribe to. To supplement our data, we obtain prices and other characteristics of cable TV services from the *Television and Cable Factbook 2006* by Warren Communications News. The average reported prices for cable TV are actually quite close to the published prices. Table 2 has the mean reported prices and the mean

Figure 1 Percentage of Independent Providers Among All DSL Subscribers

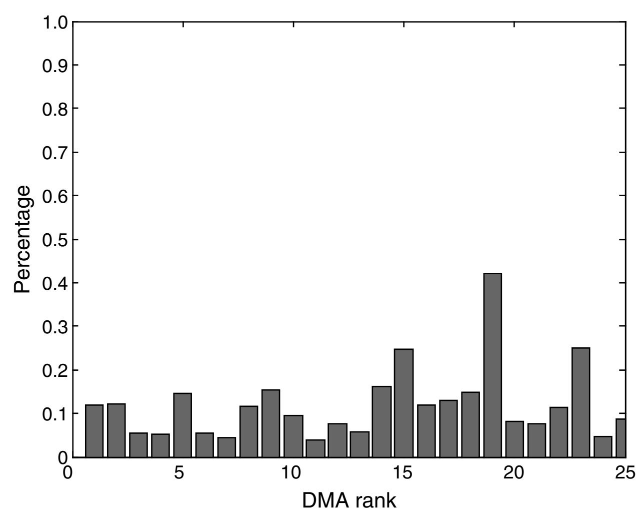


Table 2 Average Reported Prices and Published Prices for Cable TV in 2006

	Average price	
Provider	Reported	Published
Comcast	51.44	51.54
Time Warner	52.02	52.36
Charter	49.98	50.13
Cox Communications	48.79	49.46
Adelphia	49.87	49.82
Cablevision	57.56	56.95

published prices for major cable companies. As we can see, the differences are minimal, which gives us confidence in the average reported prices for the other services as well. In fact, the maximum deviation of reported prices from published prices in Table 2 is 1.35% for Cox Communications, indicating a close match between published prices and those reported by the panelists.

In our data a vast majority of cable modem subscribers also subscribed to cable TV, and most DSL subscribers also had local phone subscriptions. To infer the prices of corresponding stand-alone cable modem and DSL, we collected data on price discounts offered on bundled broadband services by different providers from their respective websites. For example, the average discount offered on bundled cable modem services was $10.06 in 2006. On the other hand, only two phone companies offered stand-alone DSL at the time—Verizon offered a discount of $10, and Qwest offered $5 on their DSL services if consumers purchased them in combination with a local phone service.

We have detailed information on households' demographics and their attitudes towards technology, family, lifestyle, etc. Table 3 displays summary statistics of the variables, including a group of indicator variables on the top, followed by the "continuous" variables. Among the indicator variables, "Technology attitude" indicates whether the survey respondent agrees to the statement "I like technology." Among the continuous variables, "Number of cable TV channels" represents the number of channels available in the expanded basic cable TV service offered by the cable company in each market. This variable comes from the *Television and Cable Factbook 2006*. Because we do not have the channel information for 2004 and 2005, we assume that the number of TV channels in each market remained stable from 2004 to 2006. Note that there is a small time-series variation in the average number of channels, which is caused by a few households who had moved during the three years.

Recall that our sample is taken as the intersection of three sets of survey respondents. To look for any potential bias caused by such selection, we report the overall means and sample means of demographic variables in Table 4. In general, the sample means are close to overall means. However, household members included in our sample are more likely to be retired—in 2006 23% of all 53,006 respondents in the United States were retired, whereas in our sample it was 4% higher. Also, households included in our sample have higher average income—in 2006 the average income was $62,890 in our sample but was 6% lower among all 53,006 survey respondents. In this study we treat

Table 3 Summary Statistics of Variables

	2004		2005		2006	
Variable	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Male living alone	0.10	0.30	0.10	0.30	0.10	0.30
Female living alone	0.07	0.25	0.07	0.26	0.08	0.26
Retired	0.26	0.44	0.28	0.45	0.27	0.45
College degree	0.33	0.47	0.32	0.46	0.32	0.46
Technology attitude	0.38	0.49	0.38	0.48	0.39	0.49
Living in a house	0.87	0.34	0.87	0.34	0.87	0.34
Having a computer at home	0.69	0.46	0.73	0.44	0.74	0.44
Having broadband at work	0.17	0.38	0.18	0.39	0.21	0.41
Household income ($000)	61.26	49.06	61.63	48.93	62.89	49.94
Household size	2.50	1.24	2.49	1.23	2.48	1.24
Number of years online	3.50	3.26	4.04	3.55	4.40	3.72
Number of cable TV channels	56.85	11.00	56.87	11.03	56.89	11.04
Monthly price						
Cable TV	44.03	5.69	48.51	5.78	50.29	5.46
Local phone	31.25	4.49	27.54	3.96	28.30	3.90
Broadband	38.15	4.54	36.57	5.20	36.12	6.36
Observations	2,590		2,590		2,590	

Table 4 Comparison of Sample Means and Overall Means

	2004		2005		2006	
Variable	Overall	Sample	Overall	Sample	Overall	Sample
Male living alone	0.09	0.10	0.11	0.10	0.10	0.10
Female living alone	0.10	0.07	0.10	0.07	0.10	0.08
Retired	0.21	0.26	0.24	0.28	0.23	0.27
College degree	0.30	0.32	0.32	0.32	0.33	0.32
Technology attitude	0.38	0.38	0.38	0.38	0.42	0.39
Living in a house	0.84	0.87	0.83	0.87	0.84	0.87
Having a computer at home	0.69	0.69	0.74	0.73	0.79	0.74
Having broadband at work	0.18	0.17	0.21	0.18	0.24	0.21
Household income ($000)	56.44	61.26	58.90	61.63	59.34	62.89
Household size	2.61	2.50	2.58	2.49	2.62	2.48
Number of years online	3.55	3.50	4.13	4.04	5.00	4.40
Observations	47,585	2,590	54,949	2,590	53,006	2,590

these differences as sampling errors and regard our sample as being random. As a caveat, we recognize that a nonrepresentative sample may cause bias in our estimates and in subsequent results. Given that the differences are small, we expect the bias to be small if present.

3. Identification

An important issue when attempting to study the complementarity across categories is separating out the effects of complementarity from the effects of preferences for the categories being studied. In other words, we can observe households making joint purchases across categories because the categories are complements or consumers have high preferences for both categories. Separating out these alternative explanations is a key challenge in this research (see also Gentzkow 2007, Sriram et al. 2010). As noted by Gentzkow (2007), there are two sources of identification that are relevant given the nature of our data—observations of households' choices over time (panel data) and exclusion restrictions.[9]

Prices are natural exclusion variables, as the price of one product does not affect the utility of another product. Thus our price variation across markets could help in identification. Also, there are variables that affect the utility of one product but not others. For example, the number of channels affects the utility of cable TV but not other products, and having high-speed Internet at work does not affect the utilities of cable TV and local phone, but it may get people familiar with broadband applications and hence increase the attractiveness of broadband at home. In addition, households in our sample may face different choice sets; e.g., for households with no computer at home, broadband does not constitute a viable option. Therefore they would be interested in cable TV and local phone only. Observing the substitution patterns within this group of households would allow us to infer consumer preferences toward cable TV and local phone, in isolation from any interaction effects with the broadband category. In addition, Petrin (2002) points out that variation in choice sets can help identify the heterogeneity in consumer preferences. Note that in our case with the access to panel data at the household level, we are also able to account for unobserved heterogeneity as well as for state dependence.

3.1. A Simulation Study

To show that we can separately identify substitutability or complementarity from consumer heterogeneity, we conduct a simulation study with 2,000 households and three years of panel data. The setup is a simplified version of our proposed model and is as follows.

Suppose there are two products, A and B, for which we are trying to estimate consumers' preferences and also to estimate the extent of substitutability or complementarity between these products. Consumers can choose one of the following options $\{0, A, B, AB\}$, where the option 0 indicates choosing neither A nor B, and AB indicates choosing both. Suppressing the time subscript, the utility derived from each option, u_j, $j \in \{0, A, B, AB\}$, is specified as

$$u_j = \bar{u}_j + \varepsilon_j, \tag{1}$$

where

$$\begin{cases} \bar{u}_0 = 0, \\ \bar{u}_A = \alpha_A + \beta p_A + \gamma x + \xi_A, \\ \bar{u}_B = \alpha_B + \beta p_B + \xi_B, \\ \bar{u}_{AB} = \bar{u}_A + \bar{u}_B + \theta. \end{cases} \tag{2}$$

α_A and α_B denote the intrinsic preferences for products A and B, respectively; β is the price coefficient, and p_A and p_B are the prices of the products. An exclusion variable x affects the utility of consuming A but not B. ξ_A and ξ_B are the unobservable (to the researcher) components of the utility function. The parameter θ measures the substitutability or complementarity between A and B. We implicitly assume that the price of AB is the sum of p_A and p_B.

We assume that ε_j follows independent standard Gumbel distributions.[10] The unobservable attributes, ξ_A and ξ_B, are distributed as

$$\begin{bmatrix} \xi_A \\ \xi_B \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_A^2 & \sigma_{AB} \\ \sigma_{AB} & \sigma_B^2 \end{bmatrix} \right). \tag{3}$$

The scale of ξ is pinned down by the logit error ε. Thus we can estimate the full covariance matrix of ξ without any normalization.

To simulate households' decisions, we need data on variables p_A, p_B, and x. We generate prices by taking random draws from a normal distribution with a mean of 1 and a standard deviation of 0.2. For the exclusion variable x, we take random draws from a Bernoulli distribution with success probability 0.5; i.e., x is a dummy variable with a 50% probability to take a value of one.

[9] Fox and Gandhi (2009) provide a formal proof under a more general setup.

[10] Ma et al. (2009) allow for a more general correlation structure. In our empirical model, we attempt to "soak up" the effects of correlated error terms by including a large set of bundle characteristics.

Table 5 Simulation Results

	200 draws		100 draws		50 draws		25 draws	
Parameter	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
$\alpha_A = 1.0$	0.998	0.122	0.994	0.119	0.984	0.123	0.968	0.117
$\alpha_B = 1.0$	0.999	0.127	0.995	0.124	0.985	0.126	0.970	0.122
$\theta = 0.6$	0.590	0.092	0.586	0.088	0.585	0.097	0.578	0.086
$\beta = -1.0$	−1.000	0.104	−0.995	0.103	−0.988	0.103	−0.974	0.101
$\gamma = 1.0$	1.002	0.068	0.997	0.068	0.988	0.066	0.974	0.067
$\sigma_A^2 = 1.0$	0.989	0.134	0.960	0.138	0.907	0.132	0.814	0.139
$\sigma_B^2 = 1.0$	0.966	0.129	0.943	0.129	0.904	0.132	0.833	0.131
$\sigma_{AB} = 0.6$	0.605	0.092	0.606	0.086	0.601	0.099	0.599	0.095

The model has eight parameters. For our simulation we use the following parameter vector:[11]

$$\begin{aligned}\Omega &= (\alpha_A, \alpha_B, \theta, \beta, \gamma, \sigma_A^2, \sigma_B^2, \sigma_{AB}) \\ &= (1, 1, 0.6, -1, 1, 1, 1, 0.6).\end{aligned}$$

Using these parameter values and the generated data, we simulate the purchase decisions, denoted by y, of 2,000 households for three time periods. At this point we have a simulated data set with observations on (y, p_A, p_B, x), which allows us to estimate the parameter vector Ω. We obtain parameter estimates using simulated maximum likelihood (SML), using 200 random draws to simulate the multivariate distribution in Equation (3).

Instead of reporting the parameter estimates in one simulation along with the asymptotic standard errors, it is more informative to repeat this experiment for a number of times and examine the small sample properties. Therefore we conduct 100 replications and obtain 100 sets of parameter estimates, with the mean and standard deviation reported in Table 5. We can see that the parameters are well recovered. An interesting issue is whether the estimation procedure is sensitive to the number of draws used to simulate the multivariate distribution. We find an increasing downward bias in the variance estimates as the number of draws decreases. Other parameters are reasonably robust to the number of draws.

3.2. Indications of Complementarity in the Data

Having demonstrated that complementarity can be recovered by estimating a version of our model, we turn to how the data (again from the simulation) might provide indications of complementarity. Suppose we want to demonstrate the presence of complementarity via a controlled experiment. We can randomly assign people to two groups. Through random assignment we expect these two groups of people to have similar preferences over product B. A priori they should have similar probabilities of purchasing B. Now to one group we give product A for free. If having product A increases the probability of purchasing product B, then we have evidence of complementarity.

In an experimental setting, we could use random assignment to control for consumer heterogeneity. This becomes impossible in real data. However, we can use exclusion restrictions in the same spirit. In our simulation study, the dummy variable x affects the utility of consuming product A but not B. Ceteris paribus, the propensity to purchase B should be the same for those with $x = 1$ and those with $x = 0$. However, if the two products are complements, the higher propensity to purchase A for those $x = 1$ would induce a higher propensity to purchase B as well.

Is this observation consistent with the simulated data? In each simulated data set, we separate the households into two groups: those with $x = 1$ and those with $x = 0$. The two groups have roughly the same size because x is randomly drawn from a Bernoulli distribution with a 50% success rate. We record the percentage of households who purchase product B in each group. The mean and standard deviation after 100 simulations are reported in Table 6.

We can see that those with $x = 1$ are more likely to purchase product B, which provides some evidence

Table 6 Indications of Complementarity

	$\theta = 0.6$		$\theta = 0$	
	Mean	Std. dev.	Mean	Std. dev.
Percentage of households purchasing B				
$x = 1$	0.589	0.009	0.500	0.010
$x = 0$	0.566	0.010	0.499	0.010
Binary logit model of purchasing B				
Intercept	1.066	0.127	0.818	0.133
p_B	−0.800	0.123	−0.823	0.125
x	0.096	0.048	0.005	0.050

[11] Actually, a wide range of parameter values can be recovered. We chose integer values for Ω to facilitate comparisons. The expected market shares for 0, A, B, and AB are 20%, 22%, 14%, and 43%, respectively, with the higher market share of AB reflecting the joint effect of complementarity and positive preference correlation.

of complementarity between A and B. In comparison, we run another 100 simulations with no complementarity; i.e., $\theta = 0$. There is no significant difference in the percentage of households purchasing product B in the two groups. With each simulated data set we can similarly estimate a binary logit model of product B purchase on x and p_B. If the two products are independent, we expect x to have no impact on product B purchase, whereas on the other hand, if the two products are complements, we expect x to have a positive impact. As shown in Table 6, this is again confirmed in our simulated data.

In summary, our simulation study confirms that we are able to separate complementarity from positive correlation in household preference. Also, it is important to note that certain data patterns can offer preliminary evidence of complementarity.

4. Reduced-Form Analysis

Before imposing a specific parametric form on the utility functions for different services, we first look for preliminary evidence of complementarity (or substitutability) by exploiting the exclusion restrictions in the data. This is important prior to engaging in full-blown model development because in the absence of such cross-category effects it may not be necessary to formulate a multicategory model, although we will still need to account for bundled discounts in the analysis in some meaningful way. As an example, we use the exclusion variable of having broadband at work to show evidence of the complementarity between broadband and cable TV. As Table 7 indicates, having broadband at work increases the probability of having broadband at home, after controlling for income. Although not reported here, the same pattern holds when we control for other observables such as education, occupation, etc. The reason might be that people with broadband at work gain knowledge about things they can do with high-speed Internet, and meanwhile they are less likely to be satisfied with dial-up Internet or no Internet at home.

Having broadband at work is unlikely to have a direct impact on cable TV subscription. Ceteris paribus, people with or without broadband at work should have the same probability of subscribing to cable TV (after controlling for heterogeneity). However, from Table 8 we see that consumers with broadband at work are more likely to have cable TV than those without broadband at work, after controlling for observable household attributes such as income. Again, this pattern repeats after we control for other forms of observed heterogeneity.

Table 7 Having Broadband at Work and at Home

	No broadband at work		Have broadband at work	
Income ($000)	Total	Home broadband (%)	Total	Home broadband (%)
≤50	3,471	9.4	291	38.8
>50	2,831	22.1	1,177	40.9

Table 8 Having Broadband at Work and Cable TV Subscription

	No broadband at work		Have broadband at work	
Income ($000)	Total	Cable TV (%)	Total	Cable TV (%)
≤50	3,471	53.9	291	59.5
>50	2,831	64.3	1,177	67.9

A possible explanation for the results in Table 8 is that consumers may systematically differ in their preferences for technologies. Thus households who have broadband at work could also have a higher preference for cable TV services. As noted before, one appealing aspect of the Forrester data is that we have self-reported panelist information on their attitudes toward technology products (like and dislike measures). Interestingly, even after we control for such self-reported attitudes toward technology and technology products, the higher subscription persists—Table 9 shows that, after controlling for income and technology attitude, we find higher cable TV subscription for those with broadband at work.

Obviously, we cannot control for all possible consumer characteristics. Nevertheless, the effect that consumers with broadband at work have a higher probability of subscribing to cable TV persists despite our best efforts to control for all the demographic and attitudinal variables at our disposal. Note that those having broadband at work are more likely to have broadband at home. Therefore the group of people with broadband at work has a larger percentage of home broadband subscribers than the other group. This may cause higher cable TV subscription associated with higher home broadband subscription in two ways.[12]

First, if there is complementarity between broadband and cable TV, households perceive higher value for cable TV in combination with broadband, which leads to higher cable TV subscription associated with higher home broadband subscription. Second, price discounts are often available if cable TV and cable modem are purchased together. This could also contribute to the higher cable TV subscription associated with higher home broadband subscription. Thus to infer complementarity we still need to rule out the effects of price discounts.

[12] On the other hand, after controlling for having broadband at home, whether having broadband at work does not have a clear impact on cable TV subscription. This provides an indication that the higher cable TV subscription is not directly calloused by having broadband at work but induced by the higher home broadband adoption.

Table 9 Technology Attitude, Having Broadband at Work and Cable TV Subscription

	Dislike technology				Like technology			
	No broadband		Have broadband		No broadband		Have broadband	
Income ($000)	Total	Cable TV (%)	Total	Cable TV (%)	Total	Cable TV (%)	Total	Cable TV (%)
≤50	2,482	53.4	121	59.5	989	55.3	170	59.4
>50	1,707	65.8	470	68.5	1,124	62.0	707	67.5

Table 10 A Binary Logit Model of Cable TV Subscription in 2006

Variable	Estimate	Std. err.
Intercept	−2.3891	1.2943
Retired	0.2545	0.1852
College degree	0.1489	0.1853
Female living alone	−0.4999	0.3169
Male living alone	−0.1989	0.2964
Technology attitude	−0.0818	0.1588
Household size	−0.0257	0.0751
Household income (log)	0.0525	0.1076
Living in a house	−0.0431	0.2344
Number of channels	0.0208	0.0075
Comcast	0.1736	0.1782
Time Warner	0.1365	0.2200
Charter	0.0960	0.4663
Cox Communications	0.6306	0.4779
Price of cable TV	−0.0420	0.0130
State dependence	5.0431	0.1594
Having broadband at work	0.5302	0.2117
Observations	2,590	
Log likelihood	−674	

To control for the effects of price discounts, we estimate a binary logit model of cable TV subscription. For those with cable modem services, the price of cable TV is subtracted by the price discount offered on the bundle of cable TV and cable modem.[13] The parameter estimates are reported in Table 10. After controlling for price discounts, the effect of having broadband at work on cable TV subscription is still significantly positive. This provides preliminary evidence of complementarities between broadband and cable TV.

We recognize that although we are careful to control for observed consumer characteristics, it is still possible that some other more specific form of unobservable heterogeneity is causing the higher cable TV subscription for those with broadband at work; i.e., some unobservable attributes of those with broadband at work are positively correlated with their preferences for cable TV. Although we are not aware of any other specific factors that might contribute to this correlation, such a possibility cannot be ruled out with our reduced-form analysis alone.

[13] This may actually overstate the effect of price discounts. We also tried attributing different portions of price discounts to cable TV. It does not change the conclusion.

5. Model

We now impose specific parametric forms for the utility function because our objective is to quantify the effects of various factors that contribute to the market outcomes for home broadband services. There are several ways in which we could approach the modeling task. One approach would be to think of consumers adding to their "portfolio" of services over time where in the first period they might already subscribe to one or more service and then look to add more services in subsequent periods conditional on their current portfolio. In our data, we observe households discontinuing services as well as adding them. Thus it appears that consumers are making decisions on whether to subscribe to each service in every time period; i.e., consumers have a choice vector in each time period. For our purposes here, we assume that consumers choose the subscription vector that maximizes their utility in each time period.

Our model specification comes from Gentzkow (2007), which we extend in a variety of ways as described below. Assume a household h makes simultaneous purchase decisions across M categories in time period t. In each category m, the household chooses an option j_m among $J_m + 1$ available products $\{0, 1, \dots, J_m\}$. The option 0 indicates the outside option. The indirect utility function is defined over the product vector $(j_1, \dots, j_M)$:

$$\begin{aligned} U_{ht}(j_1,\dots,j_M) = {} & \sum_{m=1}^{M} V_{ht}(j_m) + \Gamma_h(j_1,\dots,j_M) \\ & + \Phi(j_1,\dots,j_M \mid y_{h,t-1}) \\ & + \beta_h p_{ht}(j_1,\dots,j_M) + \varepsilon_{ht}(j_1,\dots,j_M). \end{aligned} \quad (4)$$

The first term on the right-hand side is the sum of base utilities obtained from each category that constitutes the bundle. The second term, Γ, represents interaction effects across different categories. The third term, Φ, captures state dependence effects. The fourth and fifth terms correspond to the price effect and a logit error, respectively. Next, we will discuss each of these components.

5.1. Base Utility Within a Category: $V_{ht}(j_m)$

The base utility of an option j_m in category m is specified as

$$V_{ht}(j_m) = \begin{cases} 0, & j_m = 0; \\ \gamma'_m x_{hj_m t} + \delta_m t + \xi_{hm} & \\ \quad + \nu_{hb(j_m)} + \eta_{ht}, & j_m > 0. \end{cases} \quad (5)$$

Here, x is the vector of household and product attributes, including a brand dummy. Thus γ_m corresponds to the effects of such attributes on consumer preferences for each product category. Because consumer preferences toward these categories might be evolving over time, we include a category-specific time trend δ_m in the utility specification.

The category-specific error term ξ_{hm} represents persistent unobserved heterogeneity in consumer preferences toward different categories. The brand-specific unobservable $\nu_{hb(j_m)}$, with $b(j_m)$ indicating the company that provides service alternative j_m, captures brand-specific variation beyond ξ_{hm}. The time-specific random shock η_{ht}, which is common across product categories, captures year-to-year variation in the utility of all products.

5.2. Interaction Effects Across Categories: $\Gamma_h(j_1, \dots, j_M)$

The interaction effects across categories can be decomposed as follows:

$$\Gamma_h(j_1,\dots,j_M) = \sum_{a=1}^{M} \sum_{b=a+1}^{M} (\theta_{h,ab} I_{j_a>0,\, j_b>0} + \lambda_{h,ab} I_{b(j_a)=b(j_b)}). \quad (6)$$

On the right-hand side, the two summation signs indicate that the operators go through every pair of categories. The first indicator function takes the value of one when the household purchases a product in both categories a and b; it takes the value of zero otherwise. Hence θ captures the synergy effect between the two categories—$\theta > 0$ ($\theta < 0$) implies intrinsic complementarity (substitutability) across categories. Recall that $b(j_a)$ denotes the company that offers the product j_a in category a. Thus the second indicator function indicates that, among the products included in the product vector, a pair of products j_a and j_b is offered by the same company. This may provide benefits to households in terms of dealing with only one service provider and paying a single bill. Such a single-provider effect is represented by λ, where $\lambda > 0$ implies a positive effect. In summary, there are two types of interaction effects—a pure cross-category effect and a single-provider effect.

5.3. State Dependence Effects: $\Phi(j_1, \dots, j_M \mid y_{h,t-1})$

Since Guadagni and Little (1983), the marketing literature has documented the presence of significant state dependence effects; i.e., a household's choices made in time period $t-1$ influence the choices made in time period t. In other words, a household's current choices may be affected by previous choices.

Let $y_{h,t-1}$ be the choice vector of a household h across all categories in time period $t-1$. If the household decides to switch away from its previous choice vector $y_{h,t-1}$, a switching cost may be incurred. This gives rise to an incentive for the household to stay with its previous choice vector. Furthermore, if a household is already subscribed to one service from a company, it might be easier for the company to promote its product bundle to the household. To control for such factors leading to the dependence of current choices on previous choices, we include the following terms into the specification in (4):

$$\begin{aligned} \Phi(j_1,\dots,j_M \mid y_{h,t-1}) = {} & \kappa I_{y_{h,t-1}=(j_1,\dots,j_M)} \\ & + \sum_{m=1}^{M} \tau_m I_{b(j_m)\in B(y_{h,t-1})}. \end{aligned} \quad (7)$$

κ captures the inertia in households' choice behavior; i.e., households tend to stay with their current choices because switching costs may be incurred if any adjustment is made to the choice vector. In addition, a company that is already providing a particular service to a household has natural advantages in marketing its existing service and in cross-selling its other services to the same household. Such effects are captured by the second term on the right-hand side. $B(y_{h,t-1})$ gives the set of all companies that provide services to household h in time period $t-1$, and hence $b(j_m) \in B(y_{h,t-1})$ indicates that product j_m is provided by an existing service provider to household h. Therefore, for each product j_m in the choice vector $(j_1, j_2, \dots, j_M)$, if j_m is provided by an existing provider, it has a natural advantage measured by τ_m. In other words, τ_m reflects the tendency of households to stay with the same service provider for additional services. One could also think of this term as reflecting potential contractual obligations of a subscriber toward a provider that prevents switching from that provider.

5.4. Price Effect and Logit Error

The fourth term on the right-hand side of Equation (4) is the price effect. The term p_{ht} is defined as the total price of the product vector $(j_1, \ldots, j_M)$ faced by household h at time t. Note that a price discount may be available if two or more services are purchased from the same provider.

The last term on the right-hand side of Equation (4), ε_{ht}, is a household- and time-specific demand shock for the product vector $(j_1, \ldots, j_M)$. It is assumed to follow independent standard Gumbel distributions. Although ε_{ht} is assumed to be independent across product vectors, other error components such as ξ_{hm}, ν_{hb}, and η_{ht} could induce corrections in household preferences for different product vectors. Given a household's persistent taste vector $\alpha_h = (\xi_h, \nu_h)$, we can integrate out η_{ht} and obtain the probability that the household chooses a product vector $(j_1, \ldots, j_M)$:

$$P[y_{ht} = (j_1, \ldots, j_M) \mid \alpha_h] = \int \frac{\exp[\bar{U}_{ht}(j_1, \ldots, j_M)]}{\sum_{k_1=1}^{J_1} \cdots \sum_{k_M=1}^{J_M} \exp[\bar{U}_{ht}(k_1, \ldots, k_M)]} \, dF(\eta_{ht}). \quad (8)$$

Here, $\bar{U}_{ht}(j_1, \ldots, j_M) = U_{ht}(j_1, \ldots, j_M) - \varepsilon_{ht}(j_1, \ldots, j_M)$ is the mean utility of the product vector net of the logit error ε_{ht}, and we assume η_{ht} to be independent of α_h.

5.5. Initial Conditions and Likelihood Function

In essence, Equation (8) can be rewritten as $f(y_{ht} \mid y_{h,t-1}, \alpha_h, z_t)$, which is the density function of y_{ht} conditional on the lagged decision $y_{h,t-1}$, the persistent taste α_h, and observed household and product attributes $z_t = (x_t, p_t)$. Therefore the conditional density of $(y_{h1}, \ldots, y_{hT})$ is given by

$$f(y_{h1}, \ldots, y_{hT} \mid y_{h0}, \alpha_h, z) = \prod_{t=1}^{T} f(y_{ht} \mid y_{h,t-1}, \alpha_h, z_t). \quad (9)$$

Note that this density function is conditional on the initial state y_{h0}. Now, if the initial state is fixed or exogenous, we can simply integrate out α_h to obtain

$$f(y_{h1}, \ldots, y_{hT} \mid y_{h0}, z) = \int f(y_{h1}, \ldots, y_{hT} \mid y_{h0}, \alpha_h, z) \, dF(\alpha_h). \quad (10)$$

Then we can maximize the likelihood function for all households and get consistent parameter estimates.

However, in many cases the sample data do not contain the entire purchase history of households, and hence the "initial" state y_{h0} is actually determined by the process generating the sample data. In such cases y_{h0} is not fixed or exogenous, and hence y_{h0} is stochastically dependent on (α_h, z). Therefore we cannot construct the likelihood function by performing the integration in Equation (10). This gives rise to the initial conditions problem.

Following Wooldridge (2001) and Erdem and Sun (2001), we can specify $F(\alpha_h \mid y_{h0}, z)$ and integrate out α_h to obtain the conditional density

$$f(y_{h1}, \ldots, y_{hT} \mid y_{h0}, z) = \int f(y_{h1}, \ldots, y_{hT} \mid y_{h0}, \alpha_h, z) \, dF(\alpha_h \mid y_{h0}, z). \quad (11)$$

Then we can use conditional maximum likelihood to get consistent parameter estimates. In this approach, we remain agnostic about the distribution of y_{h0} conditional on (α_h, z), but instead we specify the distribution of α_h conditional on (y_{h0}, z).

Specifically, we specify the intrinsic preference of choice vector $(j_1, \ldots, j_M)$ for household h to be

$$\alpha_h(j_1, \ldots, j_M) = \rho I_{y_{h0} = (j_1, \ldots, j_M)} + \sum_{m=1}^{M} (\xi_{hm} + \nu_{hb(j_m)}) I_{j_m > 0}. \quad (12)$$

Note that only the first term on the right-hand side of Equation (12) is additional to the utility specification (4), and the second term is already included in the base utility (5). After incorporating Equation (12), the utility specification (4) becomes

$$\begin{aligned} U_{ht}(j_1, \ldots, j_M) &= \sum_{m=1}^{M} V_{ht}(j_m) + \Gamma_h(j_1, \ldots, j_M) + \Phi(j_1, \ldots, j_M \mid y_{h,t-1}) \\ &\quad + \rho I_{y_{h0} = (j_1, \ldots, j_M)} + \beta_h p_{ht}(j_1, \ldots, j_M) + \varepsilon_{ht}(j_1, \ldots, j_M). \end{aligned}$$

We can then integrate out ξ_h and ν_h to form the conditional likelihood function:

$$\begin{aligned} L &= \prod_{h=1}^{H} f(y_{h1}, \ldots, y_{hT} \mid y_{h0}, z) \\ &= \prod_{h=1}^{H} \int f(y_{h1}, \ldots, y_{hT} \mid y_{h0}, \alpha_h(y_{h0}, \xi_h, \nu_h), z) \, dF(\xi_h, \nu_h). \end{aligned}$$

In the next section we report the estimation results based on this approach.[14]

[14] We empirically experimented with different approaches and specifications in handling the initial conditions. Our main results are not sensitive to how we deal with the initial conditions problem.

6. Results and Discussion

We apply the above model to study households' purchase decisions in three categories: cable TV, local phone, and broadband Internet access.

6.1. Empirical Specification and Estimation

A household residing in a particular geographic market is usually served by one cable company and one phone company. Thus for both cable TV and local phone, households face a binary choice of whether to subscribe to the service but have no alternative in terms of which company provides the service. To control for quality differences between service providers, each provider is associated with a separate brand intercept in each category.

In the cable TV category, we use separate intercepts for Comcast, Time Warner, Charter, Cox Communications, Adelphia, Cablevision, Insight, Mediacom, CableOne, and Bright House. All other cable companies are combined into a single group with the same brand intercept. We do not explicitly model the impact of satellite TV on the demand for cable TV, and it becomes part of the outside option for the category. Gentzkow (2007) notes that the demand estimates for the products included in our consideration set are still valid, and we are able to make accurate inferences about their relationships in demand conditional on the other goods available in the market.

In the local phone category, the major providers are AT&T, Verizon, BellSouth, Qwest, ALLTEL, CenturyTel, and Sprint. All other phone companies are combined into an "other" group with the same brand intercept.

In the broadband category, consumers may choose among five options: no broadband service, cable modem service offered by the cable company, cable modem service offered by third-party providers, DSL service offered by the phone company, or DSL service offered by third-party providers.[15]

Note that there could be multiple third-party cable modem or DSL providers for a household. In principle, all of them should be listed as separate options for the household, and there could be much more than five options in the broadband category. However, in our data the market share is small for all third-party providers combined, and in case a household has broadband from a third-party provider, we do not know the exact identity of that provider. Therefore we pool all third-party cable modem providers as a single option, and there is a single brand intercept corresponding to it. We do the same for all third-party DSL providers.

In total there are 20 ($2*2*5$) possible combinations across all three categories as listed in Table 1. Not all consumers face the same set of options though. For example, if a household does not have a computer at home, it would not be interested in any broadband service at all. Also, most consumers have no choice in their cable modem providers except for those served by Time Warner and Bright House;[16] however, AT&T and BellSouth did not offer stand-alone DSL in our data period. We are careful to allow for such variations in households' consideration sets.

According to the FCC (2005), 93% of households served by cable companies had access to cable modem services, whereas 78% of those served by phone companies had access to DSL services. Therefore we need to control for the availability issue, especially for DSL services in our estimation procedure. For that we examine all respondents to the Forrester survey for each year (not just those in our panel). If no one subscribed to DSL in a certain market, DSL service is assumed to be unavailable there. If no one subscribed to DSL from independent providers, independent DSL providers are assumed to be unavailable in that market.[17]

As we mentioned previously, consumers are heterogeneous in their preferences over the category-specific unobservable ξ_{hm}, the brand-specific ν_{hb}, and time-specific η_{ht}. We assume ξ_h to follow a three-dimensional multivariate normal distribution with a zero mean and a covariance matrix whose parameters are estimated freely (subject, of course, to the requirement of being positive-definite). As we explained in the identification simulation, it is not necessary to impose any normalization on the covariance matrix because of the logit error ε_{ht}. We assume ν_{hb} and η_{ht} to follow independent univariate normal distributions with a mean of 0. Limited by the number of observations, we estimate the heterogeneous ν_{hb} for major brands only.

We obtain parameter estimates using SML. For the SML procedure we take 200 simulation draws for each normal distribution. To draw ξ_h, which follows a multivariate normal distribution, we rely on the Cholesky decomposition of the covariance matrix. Instead of estimating the covariance matrix directly, we estimate the elements in its Cholesky decomposition.

[15] For those owning computers at home, dial-up is treated as part of the outside option; almost everyone with a computer at home could get dial-up service from at least one free source.

[16] The Federal Trade Commission (FTC) required open access to the Time Warner cable network as a condition of approving the AOL and Time Warner merger in 2000. Bright House was a part of Time Warner until 2003.

[17] We estimated the model using various assumptions on the availability issue. For instance, we could assume DSL services are available everywhere, or assume it to be available in a market as long as someone there subscribed to DSL in any of the three years. Our results are robust to these assumptions. However, we recognize that we could still overestimate the availability in case DSL was available in one part of a market but not in another.

Standard errors are obtained by taking the inverse of the Hessian matrix for the negative log-likelihood function at its minimum. We apply the delta method to get the standard errors for elements in the covariance matrix for ξ_h. Standard errors for other quantities derived later, such as price elasticities and purchase probabilities, are based on 100 simulation draws from the asymptotic distribution of the parameter estimates—we calculate these quantities at each draw and then compute the standard deviations across draws.

6.2. Results

Parameter estimates are reported in Table 11. First, brand intercepts for the top brands in each category are reported. The values of these intercepts reflect the relative attractiveness of different brands in different categories, after accounting for the other effects included in the model. Specifically, in the broadband category, preferences for cable modem services from leading cable companies are higher than preferences for DSL services from leading phone companies. This is consistent with the common perception that cable modem services offer higher quality than DSL services.

From the interactions with cable TV, we find that retired people are more likely to have cable TV, whereas household size and living in a house have a negative impact on cable TV subscription. Naturally, the number of channels increases the utility of cable TV. From the interactions with local phone, those with a college degree are more likely to have local phone at home, whereas a female living alone is less likely to have local phone service. From the interactions with broadband, the probability of broadband adoption increases with number of years online and having broadband at work.

We can also see from Table 11 that there is a negative time trend for local phone services and a positive time trend for broadband services. As the cell phone receives wider adoption, preferences for local phone might be dropping over time. Meanwhile, as more content and applications become available on the Internet, preferences for broadband would be on the rise.

Next, we turn to effects of price on households' purchase decisions. Note from Equation (4) that we allow the price effect to be household specific. In the empirical estimation, we make these price effects to vary across different income levels to see whether there are any price–income interactions in these data. Intuitively, the price coefficients show that lower income households are more price sensitive than higher income households.

Now we calculate the average price elasticity of demand for cable TV. In our model, the utility function is defined over different product vectors, e.g.,

Table 11 Parameter Estimates

Variable	Estimate	Std. err.
Brand intercepts—Cable TV		
Comcast	2.4812	0.4661
Time Warner	2.5560	0.4881
Charter	2.6639	0.5266
Cox Communications	2.5974	0.5024
Brand intercepts—Local phone		
AT&T	2.3378	0.3187
Verizon	2.3961	0.3290
BellSouth	2.6489	0.3864
Qwest	2.5447	0.3643
Brand intercepts—Broadband		
Comcast	−2.1063	0.5042
Time Warner	−2.1299	0.5024
Charter	−2.3508	0.5685
Cox Communications	−2.5339	0.6204
Third-party cable modem	−2.2635	0.4935
AT&T	−2.5967	0.4452
Verizon	−2.7399	0.4424
BellSouth	−2.5540	0.5047
Qwest	−3.5500	0.5211
Third-party DSL	−2.4157	0.4242
Interactions with cable TV		
Retired	0.3375	0.1008
College degree	−0.0096	0.0961
Male living alone	−0.1761	0.1609
Female living alone	−0.2195	0.1751
Household size	−0.1187	0.0401
Technology attitude	−0.1404	0.0848
Living in a house	−0.3424	0.1284
Number of channels	0.0092	0.0039
Interactions with local phone		
Retired	0.0063	0.1232
College degree	0.2376	0.1213
Male living alone	−0.0965	0.1956
Female living alone	−0.4488	0.2040
Household size	0.0293	0.0532
Technology attitude	−0.0877	0.1068
Interactions with broadband		
Retired	−0.3232	0.1327
College degree	0.1127	0.1053
Male living alone	0.0435	0.2163
Female living alone	0.3148	0.2591
Household size	0.0251	0.0451
Technology attitude	0.1273	0.0961
Number of years online	0.1409	0.0176
Having broadband at work	0.4294	0.1114
Time trends		
Cable TV	−0.1101	0.0819
Local phone	−0.8177	0.0977
Broadband	0.1851	0.0975
Price coefficients		
Income group 1 (<22.5K)	0.0490	0.0076
Income group 2 (22.5K∼40K)	0.0466	0.0075
Income group 3 (40K∼60K)	0.0417	0.0073
Income group 4 (60K∼90K)	0.0400	0.0073
Income group 5 (>90K)	0.0357	0.0073
Single-provider effect		
Income group 1 (<22.5K)	1.1724	0.2719
Income group 2 (22.5K∼40K)	1.3702	0.2259

Table 11 (Cont'd.)

Variable	Estimate	Std. err.
Single-provider effect		
Income group 3 (40K∼60K)	1.2061	0.2076
Income group 4 (60K∼90K)	1.2292	0.2029
Income group 5 (>90K)	0.9934	0.2001
Interactions between categories		
Cable TV ∗ local phone	−0.2275	0.1405
Cable TV ∗ broadband	0.1436	0.1269
Local phone ∗ broadband	0.3931	0.2158
State dependence		
Inertia in choice vectors	1.6726	0.0596
Inertia in service providers	1.1877	0.0950
Initial value	0.9457	0.0777
Covariance matrix for ξ		
σ_1^2	0.0058	0.0172
σ_{12}	0.0248	0.0442
σ_{13}	−0.0306	0.0534
σ_2^2	1.2048	0.6284
σ_{23}	−0.1023	0.2962
σ_3^2	0.6912	0.4353
Standard deviation for ν		
Comcast	0.0024	0.0016
Time Warner	0.0809	0.0927
Charter	0.1616	0.6746
Cox Communications	0.2510	0.2076
AT&T	0.0341	0.0235
Verizon	0.1261	0.1461
BellSouth	0.1563	0.0705
Qwest	0.1635	0.1743
Standard deviation for η	0.0002	0.0131
Observations	5,180	
Log likelihood	−6,006	

cable TV, local phone, DSL; or cable TV, no local phone, cable modem. Consequently, the purchase probability of cable TV has to be obtained by aggregating the purchase probabilities of all product vectors that include a cable TV subscription. Therefore, for each household in each time period, we calculate the own price elasticity as the expected percentage change in the purchase probability of cable TV relative to one percentage change in cable TV price.

We find that the average price elasticity for cable TV is −1.32 with a standard error of 0.21. In comparison, Goolsbee and Petrin (2004) report an own-price elasticity of −1.53 for expanded basic cable, which is within the 95% confidence interval of our estimate. Goolsbee and Petrin use the same Forrester survey data as we do but from the year 2001. Furthermore, their estimate is obtained by exploiting cross-sectional variation in cable TV prices and subscriptions across markets in which the households reside. By contrast, our estimate is obtained by exploiting both cross-sectional and time-series variation in our panel and controls for the effects of heterogeneity and state dependence, albeit the size of our cross section is smaller than that in Goolsbee and Petrin (2004) because we only focus on the subset of households that are surveyed in all three years of our analysis. Nevertheless, the closeness of the two estimates reflects the robustness of this elasticity estimate.

The average price elasticity for local phone is estimated to be −0.58 with a standard error of 0.10. An inelastic demand for phone services has been reported by past literature (e.g., Park et al. 1983, Train et al. 1987). In particular, Train et al. find an own-price elasticity of −0.46 for flat-rate local phone services. Thus our findings seem consistent with the previous literature in this regard as well.

In addition, we calculate the average price elasticity for cable modem provided by cable companies to be −1.50 with a standard error of 0.26. Note that this average price elasticity is taken across the different competitive environments in different markets; e.g., in most markets there is no third-party cable modem provider, although in some other markets DSL service is not available. Similarly, the average price elasticity for DSL provided by phone companies is −1.21 with a standard error of 0.21. We are not aware of other studies that have computed these elasticities in order to provide a comparison.

The real departure from previous literature is in terms of the estimation of across category effects. In this regard, we can see from Table 11 that there are strong single-provider effects, which indicate that consumers value the benefits from paying a single bill and dealing with a single service provider—be it for cable TV and cable modem or for local phone and DSL.[18] Again, we allow the single-provider effect to vary across income levels, and find some variations across different groups. The magnitude ranges from 0.9934 to 1.3702. On the other hand, we find that the interaction effects between categories—cable TV and broadband, cable TV and local phone, and local phone and broadband—are statistically insignificant. In other words, we do not find significant intrinsic synergies between categories.[19]

The strong single-provider effect is actually consistent with the pattern in the data. For example, in 2006 331 households had cable modem from cable companies, 95% of which had cable TV. In comparison, 346 households had DSL from phone companies, and only 52% of them had cable TV. This gives some very

[18] We had to impose a common single-provider effect across all category pairs because of the paucity of such observations in the data.

[19] We could also allow the between-category synergy effects to differ across income levels. We found some variations in these effects, but most estimates remained insignificant. Other parameter estimates are not affected in any substantial way. Therefore we report the results without heterogeneity in the between-category synergy effects, which is consistent with using the Bayesian information criterion as a criterion for model selection.

crude indication of the single-provider effect. It is possible that the difference is caused by alternative factors such as heterogeneous brand preferences, which we have controlled for in our model.

We find strong state dependence in the choice vector and in the service provider, which suggests that not only do households show a strong tendency to stay with their current choices, but they are also more likely to purchase additional services from their current service providers. In terms of the magnitude, the state dependence effect in the choice vector $\kappa = 1.6726$ dominates the single-provider effects, whereas the state dependence effect in the service provider $\tau = 1.1877$ is comparable with the single-provider effects.[20] The effect of initial value is estimated to be 0.9457, which shows that it is very important to incorporate the information contained in consumers' initial choices when modeling panel data with state dependence.

From the estimates for the covariance matrix for ξ, we can see that after controlling for the observed household and product characteristics, there is much less heterogeneity in consumer preference in the cable TV category than in the other two categories. Also, we do not find significant preference correlation between any two of the three categories after controlling for the effects of observed factors as well as cross-category and state dependence effects. Similarly, from the standard deviations for ν and η, we do not find substantial heterogeneity in terms of the brand-specific and time-specific unobservables.

6.3. Discussion

Note that the parameter estimates in Table 11 do not reflect the marginal effects on purchase probabilities. Instead, they correspond directly to the changes in latent utilities. To see the marginal benefits of the single-provider effect to phone companies, we compute the average purchase probabilities in 2006 with and without the single-provider effect, or in other words, how the purchase probabilities of each product vector would be affected if households did not benefit from the single-provider effect anymore.

In the first column of Table 12, we report the average purchase probabilities of all households in the presence of the single-provider effect. In the second column, we report the average purchase probabilities assuming zero single-provider effect in the market, i.e., assuming different companies as providers of different services. By comparing the two columns, we can see that the absence of the single-provider effect would reduce the market share of DSL services from 12.97% to 7.43%, which represents a 5.54% drop in absolute share or a 43% share decline.

We recognize that in the absence of the single-provider effect, companies may price their broadband and related services differently. However, in the above analysis we focus on the direct impact of losing the single-provider effect for phone companies while assuming all prices remain unchanged. A more complete analysis would involve a pricing model, which is beyond the scope of this study.

Similarly, we can examine the impact of state dependence on households' purchase behaviors. Because phone companies had been providing local phone and DSL services before independent DSL providers started to offer broadband services, state dependence in choice vectors and in service providers could contribute to the advantage enjoyed by phone companies over independent DSL providers. Therefore we compute the average purchase probabilities of each alternative under the assumption of no state dependence. The market share of the DSL services offered by phone companies would drop from 12.97% to 9.02%, which represents a 3.95% drop in absolute share points or a 30% share decline. Indeed, state dependence played an important role.

Another driver for households to purchase broadband services within a bundle is the price discounts offered by cable companies and phone companies. To see the marginal effects of such price discounts on purchase probabilities, we calculate the average purchase probabilities of all households in the counterfactual situation in which no price discount would be offered by phone companies when households subscribe to local phone and DSL together, or in other words, the price of a bundled DSL service would be raised to the same level as the corresponding stand-alone service.[21] The results are reported in the third column of Table 12.

We can see that if phone companies do not offer price discounts on product bundles, the market share of their DSL services would be reduced from 12.97% to 10.29%, which represents a 2.68% drop in absolute share points or a 21% share decline. In comparison, the single-provider effect dwarfs the effect of price discounts for phone companies.

According to a recent study by McKinsey & Company,[22] when asked for their motivation to purchase wireless services within a bundle, 28% of consumers cited "for the convenience of having one bill," 17% stated "for the convenience of having one customer

[20] Again, we had to impose a common effect across categories for the state dependence effect in the service provider.

[21] For Verizon and Qwest, we know the prices for their stand-alone DSL services. For other providers that did not offer stand-alone DSL, we raise their DSL prices by $10.

[22] McKinsey & Company technology external advisory board presentation, 2008.

Table 12 Comparison of the Single-Provider Effect, Price Effect, and Effect of State Dependence

	Average purchase probability							
Broadband option	With all effects		No single-provider effect		No price discount		No state dependence	
In-house CM	0.1366	(0.0058)	0.0934	(0.0077)	0.1436	(0.0062)	0.0983	(0.0080)
In-house DSL	0.1297	(0.0073)	0.0743	(0.0093)	0.1029	(0.0081)	0.0902	(0.0094)
Third-party CM	0.0033	(0.0010)	0.0048	(0.0014)	0.0036	(0.0010)	0.0077	(0.0022)
Third-party DSL	0.0154	(0.0022)	0.0227	(0.0036)	0.0167	(0.0024)	0.0374	(0.0055)

service number to call," and 23% said "to get a discount." This is consistent with our finding that the single-provider effect is more prominent than the effect of price discounts.

6.4. Model Fit

To measure model fit, we separate the 2,590 households in our panel data set into two parts—we use a random subset of 2,090 households for estimation and the rest to assess model fit.

The parameter estimates with 2,090 households are close to those with 2,590 households, although the standard errors are mostly larger. Using these parameter estimates, we compute the expected probability of each alternative being chosen by each household in the 500 hold-out sample. The alternative with the highest expected probability is taken as the predicted choice. We then compare the predicted choices and the observed choices to determine the hit rate, which we use as a measure of the model fit.

In the three product categories, namely cable TV, local phone, and broadband, the hit rates are 91.4%, 85.0%, and 84.6%, respectively for 2006. In terms of the bundle of all three categories, the hit rate is 67.4%. Although the out-of-sample fit is not perfect, the model is able to predict households' choices reasonably well. The detailed results for the full model are reported in the last column of Table 13.

There are several important components of our model, including unobserved heterogeneity, complementarity, and state dependence. To demonstrate the impact of each component, we estimated special subcases of the full model with 2,090 households and then examined how well they predict in the 500 holdout sample.

First, we estimated homogeneous logit model with no heterogeneity, complementarity, or state dependence. At the bundle level, the hit rate is 29.4% for 2006. This is indicated in the first column in Table 13. After we add consumer heterogeneity terms (i.e., ξ, η, and ν), the model fit in terms of the hit rates improves somewhat, whereas the log likelihood increases substantially. Once we add the complementarity terms (i.e., λ and θ), the log likelihood increases moderately but model fit in terms of the hit rates, especially the hit rates for the product bundles, improve significantly. A further boost comes from the state dependence parameters (i.e., κ, τ, and ρ), which allow

Table 13 Hit Rates of Different Submodels

Submodel	Submodel	No.1	No.2	No.3	No.4
	Heterogeneity		✓	✓	✓
	Complementarity			✓	✓
	State dependence				✓
	Log likelihood	−7,396	−5,266	−5,218	−4,852
Model fit 2005	Cable TV (%)	55.8	70.0	72.8	90.2
	Local phone (%)	83.2	59.4	76.4	84.2
	Broadband (%)	79.2	82.2	83.8	84.8
	Cable TV and local phone (%)	46.2	48.6	64.2	76.2
	Cable TV and broadband (%)	44.4	62.4	62.8	77.4
	Local phone and broadband (%)	64.6	51.6	64.6	71.6
	Bundle of all three (%)	36.6	44.4	55.0	65.8
Model fit 2006	Cable TV (%)	55.8	70.6	88.2	91.4
	Local phone (%)	75.6	56.0	78.6	85.0
	Broadband (%)	74.0	77.0	79.6	84.6
	Cable TV and local phone (%)	42.2	44.2	68.8	78.2
	Cable TV and broadband (%)	40.8	59.2	71.0	78.6
	Local phone and broadband (%)	52.4	46.0	62.8	72.2
	Bundle of all three (%)	29.4	38.0	55.8	67.4

Figure 2 Predicted Adoption Rates of Different Submodels

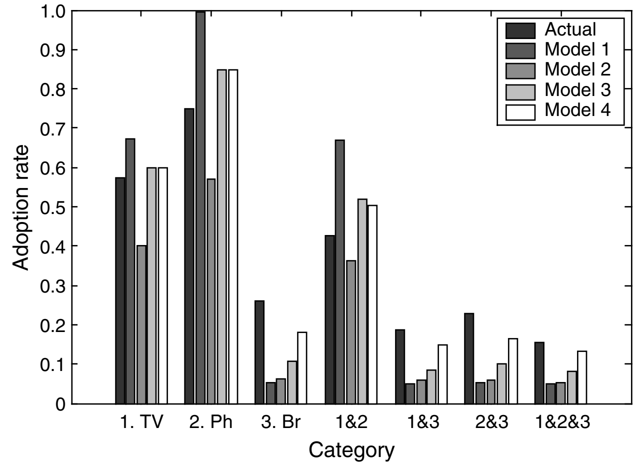
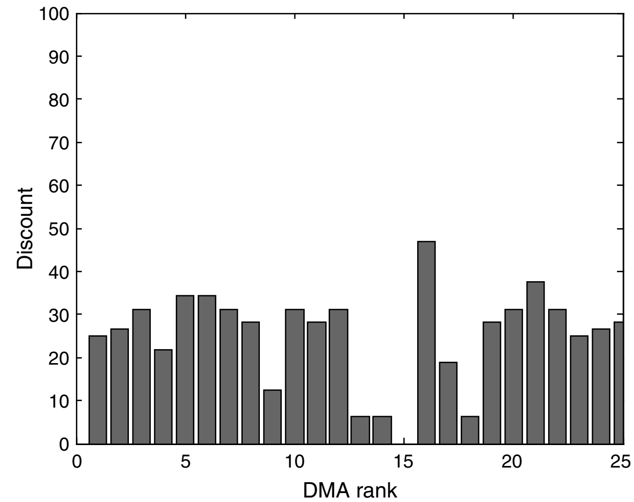


Figure 3 Price Discounts Needed for Independent Providers to Get 25% DSL Subscribers



the full model to predict 67.4% of the bundle choices for 2006.

To examine the pattern of coadoption across the households, in Figure 2 we plot the actual and predicted shares of the seven services and service combinations from Table 13 for the year 2006.[23] The full model (model 4) again seems to be performing the best among the various specifications, and the shares predicted by the full model are close to the actual shares.

7. Policy Simulations

7.1. Price Discounts Needed for Independent ISPs to Achieve a Target Market Share

From our estimation results, we can see that phone companies' large share among DSL subscribers is partially due to their offering services in multiple product categories. In our first counterfactual experiment, we calculate the price discounts that independent DSL providers would have to offer in order to overcome the single-provider effect enjoyed by phone companies. To compute this, we first specify a "target" market share level. Then, we calculate the break-even level of price under the assumption that competitors will not change their prices—a very strong assumption in and of itself. We find that, on average, independent providers would have to offer a discount of $21.86 in order to have 25% of all DSL subscribers. Table 3 shows that this is a very large discount relative to the average broadband prices in the market—a reflection of the strength of the single-provider effect and state dependence.[24]

[23] The pattern is similar for 2005.

[24] Note that these price discounts would push prices beyond the range of data. As pointed out by Montgomery and Bradlow (1999), the model assumption on linearity in price may no longer hold and the uncertainty in functional form can be larger. Such factors could cause biases in our results here.

Given that different phone companies and independent ISPs operate in different markets with these firms all having different levels of intrinsic preference, the necessary price discount computed above would vary by market. In Figure 3, we plot the price discount by market. The variation is mostly caused by the quality of DSL services offered by phone companies in different markets. For example, the DSL services offered by Qwest has a lower level of preference relative to some of the other phone companies (see Table 11), and hence independent providers would offer smaller price discounts in the markets served mostly by Qwest (e.g., DMA 13–15).

As the independent DSL provider's market share grows, its service quality or brand equity may also improve accordingly. Therefore, when calculating the price discount needed for a third-party provider to achieve a certain market share, the amount can be overstated if such scale effects are not incorporated. To estimate the impact of an improvement in consumer preference toward the third-party DSL, we assume that the brand preference for third-party DSL providers would go up from -2.4157 to -2.1063, which makes it on par with the highest brand preference in the broadband category—for the Comcast cable modem. The average price discount necessary for third-party providers to get 25% of all DSL subscribers would become $16.07, $5.79 lower than the $21.86 in the original calculation.

On the other hand, if competitors cut prices in response to the growing market share of a third-party DSL provider, the third-party provider would have to offer a larger discount to achieve a certain market share. To see the impact of such competitive reaction, we assume a 10% reduction in prices of competing broadband options and then calculate the price discount needed for third-party providers to have 25% of all DSL subscribers. The average discount necessary would become \$24.52, \$2.66 higher than the \$21.86 required in the original case.

If we assume both scale effects and competitive reaction as described above, the average price discount needed by third-party providers to have 25% of all DSL customers would be \$18.37, which is \$3.49 lower than the \$21.86 in the original case.

7.2. Impact of the FCC Deregulation

Finally, we are interested in the impact of deregulation by the FCC. In August 2005, the FCC reclassified the DSL service, and phone companies were no longer required to share their DSL network. The intention was to encourage investments and innovation from phone companies so that consumers would be better off in the long run. However, in the short term, many independent DSL providers might collapse, which would leave consumers with fewer options.

To evaluate the full impact of this FCC deregulation, we have to model phone companies' investment decisions and independent ISPs' entry and exit decisions. Also, we need information on marginal costs to understand and predict firms' pricing behavior. Given these difficulties, we take a limited approach and estimate the short-term impact only.

In particular, we examine a counterfactual situation in which all independent DSL providers are taken away while other companies maintain their prices in 2005. We calculate the compensating variation as a measure of the welfare change. The compensating variation corresponds to the dollar amount that consumers need to be compensated to maintain the same level of utility as before. Following Small and Rosen (1981), an individual household's change in welfare can be calculated by

$$\frac{\log \sum_{j_1',\ldots,j_M'} \bar{U}_h(j_1',\ldots,j_M') - \log \sum_{j_1,\ldots,j_M} \bar{U}_h(j_1,\ldots,j_M)}{\beta_h}.$$

We then integrate over all households in our panel and project our estimate to the 108 million U.S. households. The direct welfare loss is estimated to be a moderate \$493 million per year compared to total broadband revenues of \$15.0 billion. This is not surprising given the fact that independent DSL providers accounted for only 4.7% of all DSL subscribers in 2005.[25]

Because phone companies might raise prices of their DSL services as a result of the deregulation, we are interested in the change in consumer welfare when DSL prices indeed go up. At a 10% price rise for DSL services from phone companies, the compensating variation is calculated to be \$1.0 billion, about half of which can be directly attributed to the removal of independent DSL providers and half to the price rise.

8. Conclusions

Our objective in this paper was to answer the question: Besides the various supply-side explanations that have been advanced for the relatively poor showing by independent ISPs in the U.S. market, can we identify some additional demand-based explanations as well? If we only focus on the consumers' demand on broadband, we may erroneously attribute the dominance by phone companies to consumers' extremely high preference to the phone companies' broadband service. However, because the DSL service is a relatively homogenous product and a large number of third-party DSL providers offered award-winning service quality, it is hard to interpret the strong preference estimated from this demand model. Therefore, we extend our analysis to include other related products offered by the incumbent service providers. Because the choice of a broadband service might be linked to a household's purchase of other services such as local phone and cable TV as a result of bundled price discounts and to complementarity or substitution effects across these categories, we formulate a multicategory demand model for the purpose. Using panel data on households' subscription decisions on cable TV, local phone, and broadband Internet access, we estimate a multicategory mixed logit model to study consumer preferences across these categories. We find strong complementarities between broadband and the other two categories, after controlling for the effects of prices and preference correlations. The main source of such complementarities was found to be the benefits of having a single provider for multiple services.

There are several major reasons for consumers to purchase broadband services within a product bundle, including the single-provider effect, state dependence, and price discounts. Collectively, these factors give us a demand-side explanation for why independent DSL providers seem to have struggled to gain a substantial foothold in the broadband market. Furthermore, we show that the impact of the single-provider effect dominates the impact of other factors in our data.

Both complementarity and correlation in consumer preferences can affect firms' incentives for bundling (Shy 1996, Carlton and Perloff 2004). If demands for two products are interrelated, i.e., the price of one

[25] After the removal of independent DSL providers, part of the welfare loss may be attributed to the absence of state dependence effect for those households who had DSL services from independent providers. Holding all other variables constant, if we allow households to make new subscription decisions under the new market condition for one year and then calculate the welfare loss for the next year, the welfare loss would become \$243 million.

product affects the demand for the other product, it may be profitable to offer product bundles. Also, when consumers are heterogeneous and their preferences over two products are negatively correlated, bundling can be used as a method of price discrimination. Therefore, going forward, our framework and results can be useful for firms to design optimal bundling strategies.

In summary, this paper provides a plausible demand-side explanation for a particular market outcome in the U.S. broadband market. Our paper is different from other studies on the broadband market in the following ways: First, instead of focusing on consumers' demand on broadband exclusively, we explore consumers' consumption of technology across product categories. Second, unlike most previous papers on broadband adoption, which study intermodal competition (cable modem versus DSL; see, e.g., Aron and Burnstein 2003), we are interested in both the intermodal and intramodal (independent ISPs versus phone or cable companies) competition. Third, we use consumer panel data to identify the state dependence, consumer heterogeneity, and complementarity or substitutability between categories. Our results indicate strong complementarities between product categories as a result of the single-provider effect. Such cross-category effects could have contributed to the failure of independent DSL providers that could not leverage such effects given their status as single-service providers.

Acknowledgments

The authors thank Jean-Pierre Dubé, Jeremy Fox, Günter Hitsch, Peter Rossi, and the seminar participants at the University of Chicago; the University of North Carolina at Chapel Hill; the University of Minnesota; the University of California, Davis; the University of Hamburg; and the Hong Kong University of Science and Technology for comments and suggestions. Financial support from the Kilts Center for Marketing and the Kauffman Foundation for entrepreneurship-related research at the University of Chicago is gratefully acknowledged. This paper has improved substantially based on suggestions from the editor, the area editor, and the reviewers. All errors remain the authors'.

References

Aron, D. J., D. E. Burnstein. 2003. Broadband adoption in the United States: An empirical analysis. Working paper, LECG, Washington, DC.

Carlton, D. W., J. M. Perloff. 2004. *Modern Industrial Organization*, 4th ed. Addison Wesley, Indianapolis.

Chung, J., V. R. Rao. 2003. A general choice model for bundles with multiple-category products: Application to market segmentation and optimal pricing for bundles. *J. Marketing Res.* **40**(2) 115–130.

Crandall, R. W. 2005. *Competition and Chaos: U.S. Telecommunications since the 1996 Telecom Act*. Brookings Institution Press, Washington, DC.

Crandall, R. W., J. G. Sidak, H. J. Singer. 2002. The empirical case against asymmetric regulation of broadband Internet access. *Berkeley Tech. Law J.* **17**(3) 953–987.

Erdem, T., B. Sun. 2001. Testing for choice dynamics in panel data. *J. Bus. Econom. Statist.* **19**(2) 142–152.

Federal Communications Commission. 2006. High-speed services for Internet access: Status as of December 31, 2005. Report, FCC, Washington, DC. http://hraunfoss.fcc.gov/edocs_public/attachmatch/DOC-266596A1.pdf.

Fordahl, M. 2001. Despite demand, competitive DSL industry struggling. *Berkeley Daily Planet* (April 23), http//www.berkeleydaily.org/issue/2001-04-23/article/4509.

Fox, J. T., A. Gandhi. 2009. Identifying heterogeneity in economic choice and selection models using mixtures. Working paper, University of Chicago, Chicago; and National Bureau of Economic Research, Cambridge, MA.

Gentzkow, M. 2007. Valuing new goods in a model with complementarity: Online newspapers. *Amer. Econom. Rev.* **97**(3) 713–744.

Goolsbee, G., A. Petrin. 2004. The consumer gains from direct broadcast satellites and the competition with cable TV. *Econometrica* **72**(2) 351–381.

Guadagni, P. M., J. D. C. Little. 1983. A logit model of brand choice calibrated on scanner data. *Marketing Sci.* **2**(3) 203–238.

Hausman, J. 2002. Competition and regulation for Internet-related services: Results of asymmetric regulation. R. Crandall, J. Alleman, eds. *Broadband*. Brookings Institution Press, Washington, DC, 129–156.

Kalakota, R., P. Gundepudi, J. Wareham, A. Rai, R. Welke. 2002. The economics of DSL regulation. *Computer* **35**(10) 29–36.

Little, D., R., O. Crockett. 2001. Are the Baby Bells playing dirty? *BusinessWeek* (August 31), http://www.businessweek.com/magazine/content/01_33/b3745065.htm.

Ma, Y., P. B. Seetharaman C. Narasimhan. 2009. Modeling dependencies in brand choices across complementary categories. Working paper, University of Alberta, Edmonton, AB, Canada.

Manchanda, P., A. Ansari, S. Gupta. 1999. The "shopping basket": A model for multicategory purchase incidence decisions. *Marketing Sci.* **18**(2) 95–114.

McFadden, D., K. Train. 2000. Mixed MNL models for discrete response. *J. Appl. Econom.* **15**(5) 447–470.

Montgomery, A. L., E. T. Bradlow. 1999. Why analyst overconfidence about the functional form of demand models can lead to overpricing. *Marketing Sci.* **18**(4) 569–583.

Park, R. E., B. M. Wetzel, B. M. Mitchell. 1983. Price elasticities for local phone calls. *Econometrica* **51**(6) 1699–1730.

Petrin, A. 2002. Quantifying the benefits of new products: The case of the minivan. *J. Political Econom.* **110**(4) 705–729.

Reardon, M. 2005. EarthLink aims to evolve. *CNET News* (October 11), http://news.cnet.com/EarthLink-aims-to-evolve/2100-1034_3-5892671.html.

Red Herring. 2001. DSL providers get cut off. (April 2), http://www.redherring.com/Home/2022.

Russell, G. J., A. Petersen. 2000. Analysis of cross category dependence in market basket selection. *J. Retailing* **76**(3) 367–392.

Seetharaman, P. B., A. Ainslie, P. K. Chintagunta. 1999. Investigating household state dependence effects across categories. *J. Marketing Res.* **36**(4) 488–500.

Seetharaman, P. B., S. Chib, A. Ainslie, P. Boatwright, T. Chan, S. Gupta, N. Mehta, V. Rao, A. Strijnev. 2005. Models of multicategory choice behavior. *Marketing Lett.* **16**(3–4) 239–254.

Shen, Q., M. J. Villas-Boas. 2009. Strategic entry in dynamic markets. Working paper, University of Pennsylvania, Philadelphia.

Shy, O. 1996. *Industrial Organization: Theory and Applications*. MIT Press, Cambridge, MA.

Small, K. A., H. S. Rosen. 1981. Applied welfare economics with discrete choice models. *Econometrica* **49**(1) 105–130.

Song, I., P. K. Chintagunta. 2006. Measuring cross-category price effects with aggregate store data. *Management Sci.* **52**(10) 1594–1609.

Sriram, S., P. K. Chintagunta, M. K. Agarwal. 2010. Investigating consumer purchase behavior in related technology product categories. *Marketing Sci.* **29**(2) 291–314.

Train, K. E., D. L. McFadden, M. Ben-Akiva. 1987. The demand for local phone service: A fully discrete model of residential calling patterns and service choices. *RAND J. Econom.* **18**(1) 109–123.

Wedel, M., J. Zhang. 2004. Analyzing brand competition across subcategories. *J. Marketing Res.* **41**(4) 448–456.

Wooldridge, J. M. 2001. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.