Measuring consumer switching costs in the television industry *

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Abstract

This paper develops and estimates a dynamic model of consumer behavior with switching costs in the market for paid television services. It is hypothesized that consumer choices of cable versus satellite providers are affected by the presence of switching costs, which in turn justifies forward-looking consumer behavior. The model allows for persistently heterogeneous consumer preferences. I estimate parameters of the structural model using data on cable and satellite systems across local U.S. television markets over the period 1997-2006. Estimation results suggest switching costs indeed exist in the television industry, amounting to approximately \$109 and \$186 (in 1997 dollars) for cable and satellite systems respectively. Implications of using a static environment or consumer myopia assumptions for the

*I am deeply indebted to my supervisors Gregory Crawford and Gautam Gowrisankaran for their help at all stages of my work. I greatly acknowledge valuable advices and suggestions made by Daniel Ackerberg and Keisuke Hirano. All errors are my own.

parameter estimates are discussed. A simple supply side model is used to recover the cost structure of cable providers and then to simulate counterfactual experiments measuring the effect of satellite entry on optimal cable policy choice.

1 Introduction

This paper develops a dynamic model of consumer behavior that is used to estimate the size of switching costs in leading consumer industries. Switching costs are an important issue, both theoretically and empirically. They play a central role in the analysis of market structure and industry conduct for a variety of industries, including such high technology sectors as computer software and hardware development, banking, and telecommunications. I develop the analysis in the context of the paid-television industry, but the proposed methodology can be used to measure consumer switching costs in the context of other industries.

There is extensive discussion of pricing and consumer welfare issues in this industry, as fears of potential exploitation of natural monopoly power originally led to regulation of the industry. Further, the development of new competing technologies has opened the door for discussion of deregulation.

The importance of the paid-television industry in the modern U.S. economy is hard to overestimate. In 2007, only cable operators are expected to have total revenues of about \$75 billion nationwide. Not surprisingly, the industry is subject to careful monitoring by the Federal Communications Commission (FCC). Two striking conclusions are made in the FCC annual reports on cable industry prices. First, over the past decade, average cable prices increased by 93%, which is almost three times the inflation rate over the same period. According to the FCC, only half of the change in prices can be attributed to the increase in programming costs. Second, competition from direct broadcast satellite (DBS) operators is deemed to be ineffective.[1] Such findings are consistent with the theory of switching costs. It can be shown that in a mature market, switching costs may result in monopoly rents and sometimes even facilitate collusion by providing *focal points* for market division. Hence, being able to estimate switching costs is valuable for both firms and regulatory authorities. For the former, it helps to find an optimal tradeoff between introductory pricing and other activities that help to attract new customers and "harvesting profits by charging high prices that capitalize on but also run down the firm's existing stock of market share" (Klemperer (1995) p.515).[2] For the latter, the measure of switching costs is critical in designing social welfare maximizing policies.

The possibility of forward-looking consumer behavior in the presence of switching costs is the main difficulty in measuring the latter. Most of the previous empirical studies on switching costs assume that consumers myopically maximize current utility without considering the future effects of their choices (see Farrell and Klemperer (2007), p.1981). It is clear that switching costs emphasize intertemporal perspective of consumer choices. If the costs

[1]"DBS competition, however, does not appear to constrain cable prices - average prices are the same or slightly higher in communities where DBS was the basis for a finding of effective competition than in noncompetitive communities" (FCC report on cable industry prices, 2006, pp.1-2).

[2]It also affects product differentiation choices of multiproduct firms as well as the decision to offer multi-product lines.

are negligible, there are no significant gains from forward-looking behavior. Then consumer choices should be rationalized by current period variables only. However, if the costs are significant, consumers have more incentives to make dynamic decisions, which allow them to attain higher lifetime utility. Therefore, a consistent model of consumer behavior must account for the dynamic effects of switching costs.

Methodologically, my paper is most closely related to Gowrisankaran and Rysman (2007). In particular, the consumer dynamic programming (DP) problem is developed under a fairly similar set of assumptions, and the estimation is based on a three-level nested fixed point algorithm. The major difference is due to the source of dynamics, which requires an alternative formulation of the structural model. It is worth noting, however, that the dynamics generated by switching costs are not very different from ones that occur in the durable goods case.[3]

The remainder of the paper is structured as follows. I discuss related literature and some limitations of the previous empirical studies in Section 2. Section 3 outlines relevant institutional details of the paid-television industry. Some justification for the existence of consumer switching costs in the industry is provided. Section 4 describes the model of consumer behavior, its generalization, and potential caveats. The estimation algorithm is presented in Section 5, while Section 7 discusses identification of the structural parameters in the model. Section 6 describes sources of the data and explains

[3]If the subscription fee represents just another dimension of service characteristics (as is suggested in this paper), then switching cost would represent a "price" of a durable good. Of course, evolution of such a "durable good" characteristics over time needs to be taken into account. This similarity is also utilized by Kim (2006), who follows Gowrisankaran and Rysman (2007) more closely.

data collection procedures. Estimation results are presented in Section 8 and Section 10 concludes.

2 Literature review

While the theoretical literature on switching costs is quite rich, empirical studies are much less abundant. This is particularly regrettable as consumer switching costs exist in many markets. If substantial, they may cause a consumer lock-in effect that results in repeated purchases from the same supplier even when competing brands offer lower prices and better product quality. Perhaps the most pronounced examples of consumer lock-in due to switching costs can be found in the IT industries. Incompatibility of computer operating systems, video/audio recording technologies, or telecommunication standards in the cell phone industry makes human and physical capital investments into particular brands non-transferable when choosing alternative brands. Some examples of other industries with consumer switching costs include banking (Sharpe (1997), Kiser (2002), Kim et al. (2003)), auto insurance (Israel (2003)), airline (in relation to frequent flyer programs; Borenstein (1992)), long-distance telephone service (Knittel (1997)), and retail electricity industries (Salies (2005), Sturluson (2002)).

The limited number of empirical studies on the topic may reflect the difficulty of measuring switching costs, which are not directly observable in the data. Identification of switching costs in most of the existing empirical work relies on reduced form specifications, which are typically based on static/myopic choice models. One of the widely cited papers in the field is Shy (2002). He suggests a framework for quick and easy estimation of switching costs. Under a set of assumptions, the author shows how switching costs can be directly inferred from observed prices and market shares. Unfortunately, the underlying assumptions are very strong, and include homogenous products and static behavior on both the demand and supply side. It is important to emphasize that whenever there are substantial switching costs, the assumption of consumer myopia is likely to be violated regardless of the product type. A good explanation is provided by Klemperer (1987a), who in a simple two-period duopoly model shows that forward looking consumers recognize that the existence of switching costs allows firms to charge higher prices in later periods. Such anticipation, in turn, affects first period consumer decisions. Hence, for empirical work on switching costs it is very important to take these dynamic considerations into account.[4]

Dynamic consumer behavior may arise from different sources. One class of models of dynamic consumer behavior emphasizes the importance of learning (Erdem and Keane (1996), Ackerberg (2003), Crawford and Shum (2005), Erdem et al. (2005)). In these models, the dependence of current choices on past choices is motivated by the existence of imperfect information or consumer uncertainty about the product characteristics. Durability (Gowrisankaran and Rysman (2007), Melnikov (2001), Carranza (2006), Gordon (2006)) is another reason why dynamic considerations are important. In particular, not purchasing a good in the current period may be justified as it encapsulates an option to buy a better and/or cheaper good in the future. Hendel and

[4]It is worth noting that in this paper I do not model producers' behavior explicitly. Instead consumers' expectations of the future evolution of product characteristics are assumed to satisfy a rational expectation assumption within a bounded state space.

Nevo (2006) suggest that observed consumer behavior during sales periods may be a consequence of intertemporal substitution or simply stockpiling, which if ignored in traditional static demand analysis may cause mismeasurement of long-run price elasticities. I am aware of only two studies that use dynamic models to measure switching costs. The first is Kim (2006), who develops a dynamic model of consumer behavior in the cellular service industry. In her model, similar to the present paper, switching costs are the source of consumers' forward looking behavior. She found that switching costs are important determinants of consumer behavior in the industry. The second paper is Hartmann and Viard (2006) who develop a dynamic model of consumer behavior to measure switching costs generated by a golf reward program.

Recently, the market for paid television services offered by cable and DBS operators in U.S. has attracted the attention of several studies in economics. Crawford (2000) quantifies the effect of the 1992 Cable Act on household demand and welfare in cable television markets. Crawford (2005) empirically tests a discriminatory explanation for product bundling. Goolsbee and Petrin (2004) and Chu (2007) address the question of whether entry by DBS providers has a disciplining effect on the local cable systems. Crawford and Shum (2007) estimate the degree of quality degradation in cable television markets and the impact of regulation on a monopoly's quality choices. In all these studies the authors develop models where the demand side is modeled statically. If the maintained hypothesis about dynamic behavior is correct, then assuming a static model of demand would result in misspecification. The only paper that addresses the question of potential consumer lock-in due to the existence of switching costs in television market is Wise and Duwadi (2005). The authors use an indirect test for the presence of switching costs within a static model framework by comparing substitution between cable television and DBS for different ranges of price change. I am unaware of any dynamic model of consumer demand in the television industry.

3 Television industry: institutional details

Cable television originated in the late 1940s as a mean of delivering broadcast signals to the areas with poor over-the-air reception. It diffused widely in the 1970s when television networks began using satellite technology to deliver their content to cable systems (HBO was introduced in 1972, Showtime in 1976, ESPN in 1979).[5] Until the 1990s, local cable systems were effectively natural monopolies as they faced virtually no competition except in a few cases of "overbuilt" systems where the same location was served by more than one cable company. Competition from the C-Band satellite (a predecessor to today's DBS systems) was very limited because of extremely high setup costs.

DBS service was launched in the early 1990s and originally was most popular in rural areas where cable service did not exist. Since then the subscriber base of DBS providers has experienced rapid growth. Table 1 outlines the geographic decomposition of the DBS penetration rates from 2001-2004.

An important question is whether cable and DBS television services can

[5]GAO, 2003

Table 1: DBS penetration rates in 2001-2004

	2001	2004	Change
Rural	26%	29%	12%
Suburban	14%	18%	29%
Urban	9%	13%	44%

Source: GAO report to the U.S. Senate, April 2005

be viewed as close substitutes. There are several relevant issues. First, cable and DBS providers use different technologies to deliver broadcast signals to subscribers. The potential channel capacity of cable systems was typically smaller than the total capacity of satellite carriers. However, over time as cable providers upgraded their physical networks, the difference has narrowed considerably. Technology used by cable operators allows bundling of supplementary services, like telephone and internet services. Due to technological restrictions, DBS cannot match these offerings.

Until recently, some differences in the programming content were induced by industry regulation. Prior to 1999, when the Congress enacted the Satellite Home Viewer Improvement Act, DBS carriers were not allowed to broadcast local channels. In many cases this was considered a competitive disadvantage of satellite providers (see FCC 4th annual report on competition in markets for video programming, as of January 13, 1998).

Finally, DBS and cable operators use different quality and price setting strategies. While each cable system makes pricing and quality decisions locally, satellite operators set these variables at the national level. On the one hand, this feature of the market is not desirable for estimation purposes, as there is only time-series variation in the key variables for DBS. On the other, this property can be used to justify the use of satellite quality and price as valid instrumental variables.

There are several reasons to believe that consumers face substantial switching costs in the paid-television industry. First, one of the most obvious components of switching costs are upfront installation (connection) fees and, sometimes, equipment purchases.[6] For instance, the costs for basic equipment, installation, and one month of programming range from $185 for Primestar satellite service, for which the consumer rents equipment, up to $379 for DIRECTV's service.[7] Average professional installation of cable service in 1997 was about $40. It is worth noting that over time DBS developed a number of discount programs and equipment plans that were designed to overcome the problem of high upfront costs. For example, in many cases such costs were waived by the providers in exchange for a long term contract agreement.

Another important component of switching costs are various hassle costs associated with the choice of, and connection to, a provider. Typically, to arrange equipment installation, customer services of DBS and cable providers offer a time window for installation appointments during business hours. The requirement to meet the installer imposes a hassle cost on consumers. In addition, the decision to choose a particular provider may require market research on available offers and careful study of contract agreements. A consumer who previously subscribed to a different service may spend some

[6]Cable service typically does not involve purchasing equipment, but does include the rental of equipment.

[7]DIRECTV cost includes $199 equipment, $150 professional installation and monthly charges of $29.99 for the basic programming package.

effort to learn about a new (possibly more advanced) technology.[8]

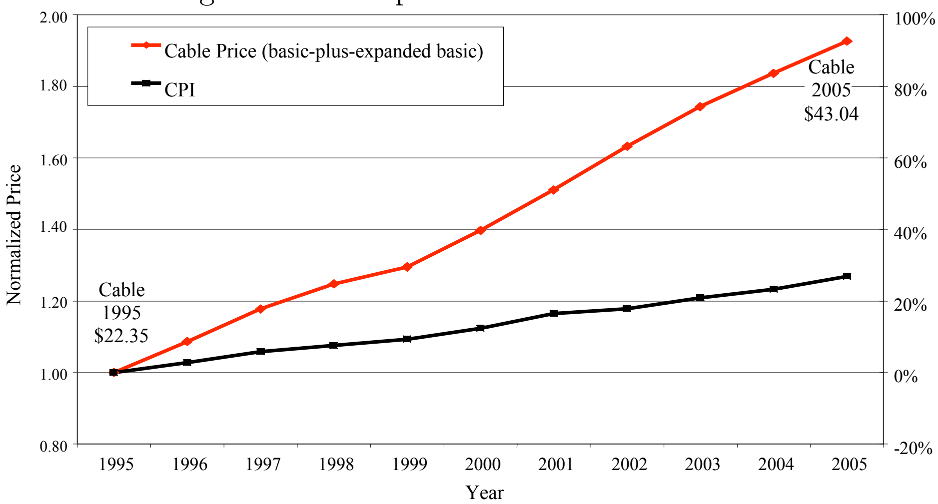
Finally, the size of the switching cost might be related to the bundling of television, telephone and internet services by cable companies. When choosing between cable and satellite a consumer may take into account that the choice of DBS would require additional effort to arrange these supplementary services. According to the industry experts, few individual consumers switch back and forth between cable and satellite television operators. Most of the switches occur when consumers move to another geographic location and, hence, must incur the startup cost regardless of the previous choice. Consumers subscribing to both cable and satellite television are rare.

Empirical evidence from consumer surveys (Nielsen Media Research survey, as cited in the 4th annual FCCcompetition report) is consistent with the assertion that consumers are locked-in by their current service providers. In particular in 1997, about 80 percent of DBS subscribers rated overall satisfaction with their service as 4 or 5 out of 5. The number of satisfied cable consumers, however, is dramatically lower at about 45 percent. Yet, according to other study (Chilton Research Services Survey, 1997 as cited by FCC), only about 10% of cable subscribers indicated that they were "very likely" to switch to DBS.

From the theoretical standpoint, switching costs may either raise or lower average oligopoly prices. The outcome critically depends on the consumer's expectations about future prices. According to Farrell and Klemperer (2007), "on balance switching costs seem more likely to increase prices" (p.1974).

[8] Very recently, this type of costs probably became negligible as the perceived difference between cable and satellite television from a consumer standpoint often boils down to a difference in design and functionality of a remote control.

Figure 1: Cable prices and CPI in 1995-2005



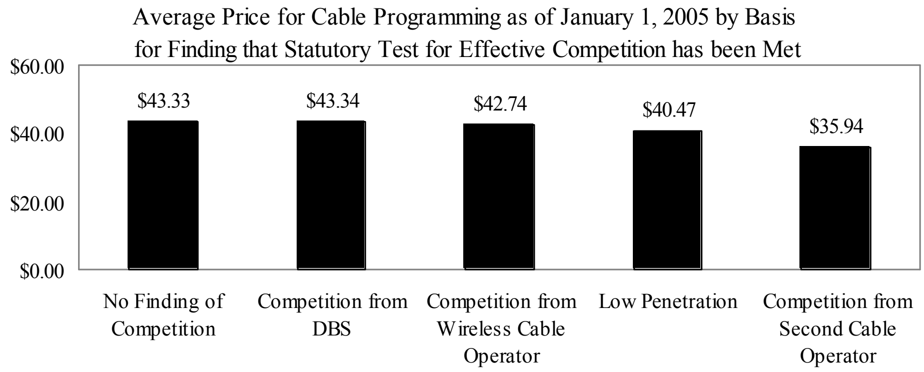
Source: FCC report on cable industry prices, 2006

In application to the television market, "bargain-then-ripoff" pricing seems plausible. In particular, many new consumers in television market can get much better deals than those who are already "locked-in". If cable companies attempt to extract rents after they have established a sufficiently large customer base, steady increases in the cable prices are consistent with the theory of switching costs (see Figure 1).

Switching costs may partially explain why cable prices in the markets with considerable competition from the DBS providers are the same or even higher than in "noncompetitive" markets (see Figure 2). According to Farrell and Klemperer (2007), a firm with a larger customer base has more incentives to exploit it. Hence, "it will usually price higher and win fewer new unattached consumers" (p.1986). Besides, consumer switching costs may facilitate collusion.[9]

[9]It is worth noting that theory provides conflicting predictions in this case.

Figure 2: Cable prices in different types of markets, 2005



Source: FCC report on cable industry prices, 2006

4 Model

Paid television is a heterogeneous service, with quality and prices varying considerably over time. A consumer facing significant switching costs needs to take into account not only current service characteristics, but also expected values of these characteristics in the future. For example, even if current period utility is low relative to the alternative, optimistic expectations about the service characteristics in the future may affect the choice of initial time subscription. Similarly, anticipation of improvement in the quality of service from the current provider may restrain consumers from switching to the rival firm when it is costly to do so.

Throughout the section I maintain the assumption that each service provider offers only one programming tier. In the last subsection, however, I extend the model to multi-product providers.

4.1 Dynamic programming problem

Consider a market for television services. The supply side of the market is represented by two firms: one cable and one satellite. The time period is indexed by t and corresponds to a calendar year. Every period each of the providers offers television service of quality q_{jt} at a monthly fee p_{jt}, where j denotes the service provider.

The demand side of the market is represented by a continuum of heterogeneous consumers indexed by i. Consumers have infinite horizons and discount the future at a common discount factor β. Each consumer may choose one of three options: cable, satellite, or over-the-air television service. The last option represents an outside alternative whose utility flow is normalized to 0.

The initial choice of either of the two systems involves a provider-specific "start-up" cost, which is similar to the definition of switching costs in Klemperer (1987a; b). The start-up costs are assumed to be constant over time and known to the consumer. These costs must be paid in the first period of cable or satellite subscription. In subsequent periods, no costs are incurred if the consumer chooses the same service provider. However, the sunk cost must be paid every time the consumer chooses a different service provider. The decision to switch to the outside alternative does not impose any costs. The presence of switching costs affects the decision problem for consumer i at time t, as it now depends on the past choice. In particular, the choice of one of the television service providers depends not only on the maximum of current utility flows attained from each of the services, but also on the size of the start-up costs. For example, a consumer who was subscribed to the cable television service in the previous period will switch to satellite only if the difference in sums of perceived discounted utility flows from the alternatives more than offsets the associated start-up cost.

Service j at time t is characterized by observed characteristics q_{jt} and p_{jt}. The variable q_{jt} stands for the quality of a bundle of channels offered by the provider. Quality depends on both the number of channels offered and the composition of individual channels in the bundle. For example, two bundles offering the same number of channels may have different quality (as perceived by consumer) depending on the composition of individual channels. The second service characteristic is the monthly subscription fee (p_{jt}). I treat the subscription fee as another dimension of (negative) product characteristics as opposed to its interpretation in terms of repeated purchases. One possible view of the model is that a consumer who has subscribed to a particular service for several periods keeps a product whose characteristics evolve over time.

In addition to the observed characteristics, there are service-specific characteristics ξ_{jt} unobserved by the econometrician. These characteristics may represent the quality of customer service in the local market, and the availability and content of the local channels. An important component of television service is the quality of the programming content offered by individual channels. Even if the composition of channels in a bundle does not change across periods, perceived quality of the content of each channel (e.g. popular shows, movies, etc.) may vary across time periods and markets. This unobserved quality variation contributes to ξ_{jt}. Another important property of television market is the difference between cable and satellite technology. In many cases, cable companies bundle their television services with fixed-line telephone and internet services, which due to technological restrictions cannot be matched by satellite competitors. The availability of these extra options can make cable service more attractive than satellite for the same level of other product characteristics. I assume that the availability of the supplementary services can be represented as the difference in means of unobserved product characteristics for cable and DBS. This is obviously a strong assumption because instances of bundling of supplementary services vary across markets and time periods.

Consumer preferences over q_{jt} and p_{jt} are defined by the consumer-specific random coefficients α_{1i} and α_{2i} respectively. The provider-specific constant term α_{0ij} accounts for the availability of supplementary services in case of cable subscription. It also includes other constant over time technology-related differences between cable and DBS providers.

Every period, a consumer who chooses satellite or cable television obtains a flow utility based on the television service currently chosen. The parametric form of the per-period flow utility is assumed to satisfy

$$U_{ijt} = \eta_j I(a_{it-1} \neq j) + \alpha_{0ij} + \alpha_{1i} q_{jt} + \alpha_{2i} p_{jt} + \xi_{jt} + \epsilon_{ijt} \quad (1)$$

where a_{it-1} is the consumer choice in the previous period, $I(.)$ is an indicator function, η_j denotes a start-up cost associated with the provider j, and ϵ_{ijt} represents an independently identically distributed (across consumers, providers and time periods) type I extreme value random variable. Switching costs are allowed to vary across providers because of the differences in up-front installation and equipment fees, bundling of supplementary services offered by cable, and the possibility that consumers' hassle costs of choosing a particular service may vary across providers. Consumers are assumed to be persistently heterogeneous in terms of their marginal utilities of product characteristics. I assume that consumer heterogeneity parameters are normally distributed with means α_1, α_2 and variances $\sigma^2_{\alpha_1}$, $\sigma^2_{\alpha_2}$ respectively. Note that ξ_{jt} is not restricted to follow any specific distribution.

Let

$$\bar{\delta}_{jt} = \alpha_{0j} + \alpha_1 q_{jt} + \alpha_2 p_{jt} + \xi_{jt} \tag{2}$$

$$\delta_{ijt} = \bar{\delta}_{jt} + \tilde{\alpha}_{1i}\sigma_{\alpha_1} q_{jt} + \tilde{\alpha}_{2i}\sigma_{\alpha_2} p_{jt} \tag{3}$$

where $\tilde{\alpha}_{1i}\sigma_{\alpha_1}$ and $\tilde{\alpha}_{2i}\sigma_{\alpha_2}$ represent deviations from the mean quality and price coefficients. Then the consumer utility function can be written as

$$U_{ijt} = \eta_j I(a_{it-1} \neq j) + \delta_{ijt} + \epsilon_{ijt} \tag{4}$$

A consumer who is not currently subscribed to cable or satellite television has flow utility normalized to zero, i.e. $\delta_{i0t} = 0$ and

$$U_{i0t} = \epsilon_{i0t}$$

The relationship between current utility flow conditional on the current and previous period choices is summarized in the table 2

In order to evaluate consumer i's choice at time t, I need to define expecta-

Table 2: Current consumer utility flow

Previous choice	**Current choice**		
	Outside	Cable	Satellite
Outside	ϵ_{i0t}	$-\eta_c + \delta_{ict} + \epsilon_{ict}$	$-\eta_s + \delta_{ist} + \epsilon_{ist}$
Cable	ϵ_{i0t}	$\delta_{ict} + \epsilon_{ict}$	$-\eta_s + \delta_{ist} + \epsilon_{ist}$
Satellite	ϵ_{i0t}	$-\eta_c + \delta_{ict} + \epsilon_{ict}$	$\delta_{ist} + \epsilon_{ist}$

tions about the evolution of the service characteristics. The IID assumption on $\epsilon_{ijt}, j \in \{0, c, s\}$ implies that at period t the consumer has no information about future values of the shocks ϵ beyond their distribution. Although consumers are uncertain about future values of service characteristics, I assume that they form expectations about their evolution as discussed next.

Let me define state variables and describe the consumer's dynamic programming (DP) problem. Let $a_{it-1} \in \{0, c, s\}$ denote the consumer choice in the previous period, let Ω_t denote current service characteristics and any other factors that affect future service characteristics, and let $\epsilon_{it} = (\epsilon_{i0t}, \epsilon_{ict}, \epsilon_{ist})$. I assume that Ω_t evolves according to a first-order Markov process $P(\Omega_{t+1}|\Omega_t)$ that accounts for the providers' optimizing behavior. Then the state vector for consumer i is $(\epsilon_{it}, \Omega_t, a_{it-1})$. Let $V_i(\epsilon_{it}, \Omega_t, a_{it-1})$ denote the value function. Under the assumption that consumers maximize the present discounted value of future utility flows, I can write the dynamic programming (DP) problem of consumer i in the form of a Bellman equation

$$V_i(\epsilon_{it}, \Omega_t, a_{it-1}) =$$

$$\max \left\{ \begin{array}{c} U_{i0t} + \beta E\left[V_i\left(\epsilon_{it+1}, \Omega_{t+1}, a_{it} = 0\right) | \epsilon_{it}, \Omega_t, a_{it-1}\right], \\ U_{ict} + \beta E\left[V_i\left(\epsilon_{it+1}, \Omega_{t+1}, a_{it} = c\right) | \epsilon_{it}, \Omega_t, a_{it-1}\right], \\ U_{ist} + \beta E\left[V_i\left(\epsilon_{it+1}, \Omega_{t+1}, a_{it} = s\right) | \epsilon_{it}, \Omega_t, a_{it-1}\right] \end{array} \right\} \tag{5}$$

where the conditional expectation is defined over the future values of state variables.

The potentially infinite dimensionality of Ω_t makes the DP problem computationally intractable. In order to reduce the number of state variables I follow an approach suggested by Gowrisankaran and Rysman (2007). In particular, I proceed with a major simplifying assumption about the marginal distributions of state variables

Assumption 1: $P(\delta_{ijt+1}|\Omega_t) = P(\delta_{ijt+1}|\Omega_t'), j = c, s$ if $\delta_{ict}(\Omega_t) = \delta_{ict}(\Omega_t')$ and $\delta_{ist}(\Omega_t) = \delta_{ist}(\Omega_t')$

This assumption implies that any given pair of current utility flows provides all relevant information about the marginal distributions of future utility flows. In other words, $P(\delta_{ijt+1}|\delta_{ict}, \delta_{ist}, \Omega_t) = P(\delta_{ijt+1}|\delta_{ict}, \delta_{ist})$, $j = c, s$. This assumption greatly simplifies the state space to $(\epsilon_{it}, \delta_{ict}, \delta_{ist}, a_{it-1})$, where ϵ_{it} has three dimensions. Obviously, it is restrictive, as there might be other information available to the consumers that is useful in defining the probability distribution over the future utility delivered by the service providers. One example of such information is government regulation of the television industry. Incorporating this information into the model would increase the state space, which is very burdensome from a computational point of view.

A further simplification can be made by using the iid extreme value assumption on the consumer idiosyncrasy, the discreteness of decisions, and the assumption that consumers know their switching costs. Since one of the state variables, a_{it-1} is discrete and indexes only three possible choices, equation (5) can be written in terms of alternative-specific value functions. Let $V_i^{kj}(\delta_{ict}, \delta_{ist})$ denote consumer value attained from choosing alternative j given previous period choice k, where $k, j \in \{0, c, s\}$, net of current idiosyncratic preference. Note that regardless of the last period choice, a consumer who chooses an outside alternative in the current period faces the same set of options in the future. Since by assumption there are no switching costs associated with this choice, I can define $V_i^{00}(\delta_{ict}, \delta_{ist}) = V_i^{k0}(\delta_{ict}, \delta_{ist}), \forall k \in \{0, c, s\}$. A consumer who chooses cable system in the current period but who was not a cable subscriber previously, will face the same set of future options and attain the same current utility level as a continuous cable subscriber of the same type. Therefore, for the same consumer type, the value of a newcomer must be the same as the value of the incumbent consumer less the start-up cost. The same holds for consumers who choose satellite in the current period. Then, I can write $V_i^{kj}(\delta_{ict}, \delta_{ist}) = V_i^{jj}(\delta_{ict}, \delta_{ist}) - \eta_j, \forall k \neq j$. Since the current draw of ϵ_{it} does not provide any information about the future (due to the IID assumption), it can be removed from the state space, which now includes only $(\delta_{ict}, \delta_{ist})$. Finally, integrating over the distribution of future ϵ_{it} and using the expected maximum property of the iid extreme values errors, I can define a joint contraction mapping similar to Rust (1987)

$$\begin{cases} V_i^{00} = \beta E \ln[\exp V_i^{00} + \exp(V_i^{cc} - \eta_c) + \exp(V_i^{ss} - \eta_s)], \\ V_i^{cc} = \delta_{ict} + \beta E \ln[\exp V_i^{00} + \exp V_i^{cc} + \exp(V_i^{ss} - \eta_s)], \\ V_i^{ss} = \delta_{ist} + \beta E \ln[\exp V_i^{00} + \exp(V_i^{cc} - \eta_c) + \exp V_i^{ss}] \end{cases} \tag{6}$$

where "E" denotes conditional expectation defined with respect to future values of state variables $(\delta_{ict}, \delta_{ist})$ (suppressed).

4.2 Expectations

Solving the Bellman equation requires specifying distributions for the state variables. Assumption 1 above suggests that the current pair of flow utilities provides all the information about marginal densities of the state variables. Consistent with the rational expectations assumption, I assume that consumer i perceives the actual empirical marginal density of δ_{ist+1} fitted to a simple autoregressive specification

$$\delta_{ist+1} = \gamma_{0si} + \gamma_{1si}\delta_{ist} + u_{ist} \tag{7}$$

Due to the difference in strategic behavior of satellite and cable operators (the former sets prices and qualities at national, while the latter at local level), expected utility flow for a cable provider is assumed to depend on the past utility flow generated by a satellite competitor.

$$\delta_{ict+1} = \gamma_{0ci} + \gamma_{1ci}\delta_{ict} + \gamma_{2si}\delta_{ist} + u_{ict} \tag{8}$$

where u_{ist} and u_{ict} are normally distributed with means 0 and variances $\sigma^2_{u_{ist}}$ and $\sigma^2_{u_{ict}}$ respectively, and $\gamma_{0si}, \gamma_{1si}, \sigma^2_{u_{ist}}\gamma_{0ci}, \gamma_{1ci}, \gamma_{2ci}$ and $\sigma^2_{u_{ict}}$ are transition parameters. I estimate (7) and (8) using ordinary least squares (see Section 5) fitted to the equilibrium data for any set of structural parameters.

4.3 Purchase probabilities and market shares

In every period, each consumer type has three choices and can be in one of the three possible states, based on the last possible choice: cable, satellite, or neither. Therefore, the joint contraction mapping in equation (6) results in nine value functions for each consumer type net of current idiosyncratic draws. Purchase probabilities that depend on the past choice can be obtained by integrating over the current draws of ϵ_{it}. In particular, the probability of choosing provider j conditional on being previously subscribed to provider k (including outside alternative) is given by

$$\begin{aligned}\Pr(a_{it} = j | a_{it-1} = k) &= \Pr(V_i^{kj} + \epsilon_{ijt} \geq V_i^{kl} + \epsilon_{ilt}, \forall l \neq j\}) \\ &= \frac{\exp V_i^{kj}}{\sum_l \exp V_i^{kl}}\end{aligned}$$

Let s_{ict-1}, s_{ist-1}, and s_{i0t-1} denote the shares of consumer type i subscribed to cable, satellite and neither in period $t-1$. Then the current period predicted market shares for the consumer i are given by the following expression

$$s_{ijt} = \sum_k s_{ikt-1} \frac{\exp V_i^{kj}}{\sum_l \exp V_i^{kl}} \tag{9}$$

where $l, j, k = \{0, c, s\}$.

Note that each $V_i^{kj}(\delta_{ict}, \delta_{ist})$, where $k, j \in \{0, c, s\}$ is a function that gives consumer type i's value (net of vector of current idiosyncratic draws ϵ_{it}) of making choice j when past choice was k at any point in the state space $(\delta_{ict}, \delta_{ist})$.

From (9), consumer i's current market share is a function of the distribution of past market shares for this type and a set of choice-specific value functions. In addition, there is a pair (one for each provider) of time invariant consumer-specific switching costs, (η_c, η_s), which does not enter the state space, but affects the value function as is shown in (6). Then the market share of consumer type i choosing provider j in period t can be written as $s_{ijt}(\delta_{ict}, \delta_{ist}, \eta_c, \eta_s)$. In turn, a pair of current flow utilities for consumer i, $(\delta_{ict}, \delta_{ist})$, is a function of the pair of the population mean flow utility $(\bar{\delta}_{ct}, \bar{\delta}_{ct})$, deviations of the type i's random coefficients, $(\tilde{\alpha}_{1i}, \tilde{\alpha}_{2i})$, from the population means and the data.

Let $\mathbf{\Theta}^n \hat{=} \{\sigma^2_{\alpha_1}, \sigma^2_{\alpha_2}, \eta_c, \eta_s\}$ be the vector of structural parameters which describe the distributions of the random quantities in the model and a pair of switching costs parameters. In order to obtain aggregate market shares I integrate over the distribution of consumer types given values of nonlinear parameters, i.e.

$$s_{jt}(\bar{\delta}_{ct}, \bar{\delta}_{st} | \mathbf{\Theta}^n) = \int s_{ijt}(\bar{\delta}_{ct}, \bar{\delta}_{st}, \tilde{\alpha}_{1i}, \tilde{\alpha}_{2i}) dF(\tilde{\alpha}_{1i}, \tilde{\alpha}_{2i} | \mathbf{\Theta}^n) \tag{10}$$

where $j = c, s$.

As it is discussed in section 5, I use a frequency simulator to approximate the multidimensional integral in equation (10).

4.4 Recovering mean utility flows

In order to recover mean utility flows I use a numerical inversion routine, similar to one developed by Berry et al. (1995) (BLP). In particular, true mean utility flows, $\bar{\delta}_{jt}$, where $j = c, s$, must solve the following system of equations

$$\begin{cases} s_{ct} = \hat{s}_{ct}(\bar{\delta}_{ct}, \bar{\delta}_{st}|\mathbf{\Theta}^n) \\ s_{st} = \hat{s}_{st}(\bar{\delta}_{ct}, \bar{\delta}_{st}|\mathbf{\Theta}^n) \end{cases} \tag{11}$$

where s_{ct} and s_{st} are observed market share of cable and satellite systems respectively, while $\hat{s}_{ct}(.)$ and $\hat{s}_{st}(.)$ are the market shares predicted by the model given the vector of parameters $\mathbf{\Theta}^n$.

In practice, I used an iterative routine that updates the values of the mean utility flows as follows

$$\begin{cases} \bar{\delta}'_{ct} = \bar{\delta}_{ct} + \ln(s_{ct}) - \ln(\hat{s}_{ct}(\bar{\delta}_{ct}, \bar{\delta}_{st}|\mathbf{\Theta}^n))) \\ \bar{\delta}'_{st} = \bar{\delta}_{st} + \ln(s_{st}) - \ln(\hat{s}_{st}(\bar{\delta}_{ct}, \bar{\delta}_{st}|\mathbf{\Theta}^n))) \end{cases} \tag{12}$$

where $\bar{\delta}'_{jt}$ is the current and $\bar{\delta}_{jt}$ is the previous iteration flow utility value.

Before discussing the estimation algorithm, consider an important property of the suggested dynamic framework. One of the goals of this paper is to measure to what extent traditional static models are misspecified if the observed data is generated by dynamic consumer behavior. In the suggested framework a dynamic model becomes identical to a static one if the switching cost parameters are set to zeros regardless of the assumption about the discount factor value. A brief formal exposition may be useful. Let $\eta_c = \eta_s = 0$ and consider the probability that consumer type i subscribes to provider j conditional on the choice of provider k in the previous period.

$$\begin{aligned}
\Pr(a_{it} = j | a_{it-1} = k) &= \frac{e^{\delta_{ijt} + \beta EV_i^j}}{e^{0 + \beta EV_i^0} + e^{\delta_{ict} + \beta EV_i^c} + e^{\delta_{ist} + \beta EV_i^s}} \\
&= \frac{e^{\delta_{ijt}} e^{\beta EV_i}}{(1 + e^{\delta_{ict}} + e^{\delta_{ist}}) e^{\beta EV_i}} \\
&= \frac{e^{\delta_{ijt}}}{(1 + e^{\delta_{ict}} + e^{\delta_{ist}})} \\
&= \Pr(a_{it} = j)
\end{aligned}$$

where the second equality comes from the fact that $EV^0 = EV^c = EV^s$. In this case, the dynamic model would result in purchase probabilities and market shares defined exactly as in the static logit model. This property of the dynamic model allows direct testing for the presence of substantial switching costs in the television industry.

5 Estimation algorithm

My method of estimating the model parameters is based on techniques developed by Berry (1994), Rust (1987) and the literature that follows. Similar to Gowrisankaran and Rysman (2007) the estimation algorithm involves three levels of optimization.

The inner loop solves the consumer DP problem in equation (5) for each consumer type and calculates predicted aggregate market shares as in equation (10). The middle loop computes the mean flow utilities that match observed market shares to the market shares predicted by the model. The outer loop searches over the parameter vector. Let me briefly describe some details for each of the stages.

In the inner loop, when solving the DP problem, instead of estimating the discount factor, β, I set its value to 0.95. To obtain a solution to the consumer problem, I use the joint contraction mapping (6) with state space discretized into 400 grid points (20 points along each dimension of the state space). In order to simulate expected continuation values, I use the linear specifications (7) and (8). In particular, for any initial guess of vectors of population mean utility flows, draws of random coefficients for the consumer i, and data, I calculate $\delta_{ijt} = \bar{\delta}_{jt} + \tilde{\alpha}_{1i}\sigma_{\alpha_1}q_{jt}$ and $\tilde{\alpha}_{2i}\sigma_{\alpha_2}p_{jt}, j = c, s$. This information is then used to update the coefficients in the linear regressions (7) and (8). In turn, these coefficients are used to simulate a two-dimensional integral on the right hand side of (6) by using quadrature with 100 grid points (10 points along each dimension). Note that the value functions for each consumer type are different not only due to the difference in the parameters used to simulate expectations but also due to the idiosyncratic draws for switching costs. After convergence for the Bellman equations is achieved, I use equation (10) to obtain predicted market shares. This procedure is iterative and may need some explanation.

First, I observe markets where both cable and satellite carriers have positive market shares. This raises an issue of initial conditions. For the model with only one consumer type, I use observed market shares as initial conditions. For the random coefficients model, I use the following algorithm to estimate the distribution of consumer types across initial conditions. For each consumer i and initial guess of $\bar{\delta}_{j0}, j = c, s$ (where $t = 0$ denotes the first period observed), I calculate δ_{ij0} as in equation (3). Then using current estimates of the transition parameters from equations (7) and (8) I predict flow utilities backwards down to 1993, which is considered to be the DBS entry year.[10] In 1993, I assume that satellite share is zero in all markets. For cable, I predict flow utilities one more step backwards and assume that the distribution of consumer types satisfy myopic choice between cable and the outside alternative, i.e. simple logit probabilities. Then I use the current solution to the consumer DP problem to predict market shares for each type simulating the path of market shares up to the first observed period in the data. This approximates the distribution of consumer types across initial conditions.

For every consecutive period, I calculate probabilities of staying and switching for each of the three states (past choices). Then these probabilities are applied to the corresponding last period market shares of type i as in as in equation (9). This procedure generates a sequence of market shares for the consumer type i. I repeat this for each of the simulated consumers. Finally, to integrate over the consumer types as in equation (10) I use the frequency simulator

$$s_{jt}(\bar{\delta}_{ct}, \bar{\delta}_{st}) = \frac{1}{NS}\sum_{i=1}^{NS} s_{ijt}(\bar{\delta}_{ct}, \bar{\delta}_{st}, \tilde{\alpha}_{1i}, \tilde{\alpha}_{2i}|\mathbf{\Theta}^n)$$

[10]This is done for each market and for each consumer type. The length of the predictions depends on the date of the first observation in the data.

For each consumer type I need to solve the DP problem numerically and for the random coefficients model I have to use backwards predictions back to 1993. This restricts the number of simulated consumers due to the computational burden. For the estimation results presented in this paper, I used 30 simulated consumers.

Note that the calculation of individual and aggregate market shares depends on the initial guess of mean flow utilities vectors. For the first iteration of the inner loop I use two vectors of zeros. After the inner loop converges, I obtain aggregate market shares that are consistent with the zero mean utility flows in every period (given data on service characteristics and current parameters' values). Now I move to the middle loop that updates the population mean flow utilities using (12). New vectors of mean utility flows are then supplied to the inner loop, which generates a new set of predicted aggregate market shares. The inner and the middle loops are repeated interchangeably until convergence in both stages. The resulting vectors of mean utility flows are then used in the outer loop which I discuss now.

The outer loop searches over the set of nonlinear parameters $\mathbf{\Theta}^n$ by solving

$$\hat{\mathbf{\Theta}^n} = \arg\min_{\mathbf{\Theta}^n} \{G(\mathbf{\Theta}^n)'WG(\mathbf{\Theta}^n)\} \tag{13}$$

where $G(\mathbf{\Theta}^n)$ is a vector of sample moments and W is the optimal weighting matrix. The vector of sample moments is based on the conditional independence assumption

$$E[\xi_{jt}|\mathbf{z_{jt}}] = 0 \tag{14}$$

and is defined as

$$G(\mathbf{\Theta}^n) = \mathbf{z}'\xi(\mathbf{\Theta}^n) \tag{15}$$

where $\xi(\mathbf{\Theta}^n)$ is the vector of unobserved product characteristics making (via $\bar{\delta}_{jt}$) predicted shares equal to the observed product shares, and $\mathbf{z}$ is a matrix of exogenous variables, described in details in section 7.

I minimize equation (13) by performing a nonlinear search over $\mathbf{\Theta}^n$. For each vector of these parameters' values, I first obtain $\bar{\delta}_{jt}$'s from sequentially iterating the inner and middle loops until convergence. Then I solve for linear parameters α_{0j}, α_1, and α_2 in closed form. In particular, since $\bar{\delta}_{jt} = \alpha_{0j} + \alpha_1 q_{jt} + \alpha_2 p_{jt} + \xi_{jt}$, I can solve for the $\hat{\alpha}_0$, $\hat{\alpha}_1$ and $\hat{\alpha}_2$ that minimize equation (13) in closed form, i.e.[11]

$$(\hat{\alpha}_0, \hat{\alpha}_1, \hat{\alpha}_2)' = (X'P_Z X)^{-1} X' P_Z \bar{\delta} \tag{16}$$

and in the second step

$$(\hat{\alpha}_0, \hat{\alpha}_1, \hat{\alpha}_2)' = \left(X'Z \left(\hat{W} \right)^{-1} Z'X \right)^{-1} X'Z \left(\hat{W} \right)^{-1} Z'\bar{\delta} \tag{17}$$

where $\hat{W}$ is the estimated optimal weighting matrix. The nonlinear search is performed using the simplex method. Final estimates of the parameters are obtained using the 2-step efficient GMM procedure.

[11]In the first step of the GMM procedure weighting matrix is set to $W = (z'z)^{-1}$

5.1 Extension to multiple tiers

Below I briefly outline an extension of the model and related identification issues. The primary reason to maintain the one-provider-one-service assumption above is not a result of theoretical difficulties of accounting for multi-product firms. With some additional assumptions the framework above can handle multi-product environments as long as the number of producers remains small. Using tier-specific information may bring more benefits than just extra observations. It turns out that in some cases, information on tier level market shares for the same provider can be used to identify some of the structural parameters without solving the DP problem.

One practical problem with multiple tiers per provider is the size of the state space. It is not feasible from a computational standpoint to include each distinct tier in the consumer state space. There are two possible solutions to the problem. The first is to divide consumer state variables into current holdings and a variable that measures the expected maximum of purchasing from all products available in a given period, as in the model developed by Gowrisankaran and Rysman (2007). Depending on whether the product belongs to the same provider (as the current holding), each of the flow utility alternatives is adjusted for switching costs. A minor difference from the setup offered by the aforementioned authors is that characteristics of the current holding (both observed and unobserved) would vary over time similar to the logit inclusive values of other options. If a monthly subscription fee is viewed as another dimension of product characteristics, switching cost can be treated as price of durable good, which may depreciate or appreciate next period.

An alternative would be to keep the present setup but to assume that consumers make their dynamic decisions under uncertainty about their tier-specific preferences. In particular, suppose that the parametric representation of consumer utility is

$$U_{ijt} = \alpha_{0j} + \alpha_1 q_{j_g t} + \alpha_{2i} p_{j_g t} + \xi_{jt} + \epsilon_{ijt} + v_{ij_g t}$$

where i, j, g, t index consumer, provider, tier, and time period respectively, q_{jt} measures programming quality, p_{jt} measures monthly subscription fee, ξ_{jt} is common-for-all-consumers provider-specific quality component unobserved by econometrician, ϵ_{ijt} represents consumer idiosyncratic preferences towards a provider, and $v_{ij_g t}$ is consumer preference towards a particular tier offered by a given provider.

Assume that prior to making the provider choice the consumer observes ϵ_{it} but not $v_{ij_g t}$. Therefore, the consumer's decision is based on expectation over the distribution of $v_{ij_g t}$. This assumption pools tiers offered by the same provider into a single variable (logit inclusive values) which then enters the state space. In particular, let

$$\bar{\delta}_{j_g t} = \alpha_{0j} + \alpha_1 q_{j_g t} + \alpha_2 p_{j_g t} + \xi_{jt}$$
$$\bar{\bar{\delta}}_{ij_g t} = \bar{\delta}_{j_g t} + \tilde{\alpha}_{1i} q_{j_g t} + \tilde{\alpha}_{2i} p_{j_g t}$$
$$\delta_{ijt} = E \max\{\bar{\bar{\delta}}_{ij_1 t} + v_{j_1 t}, ..., \bar{\bar{\delta}}_{ijG_j t} + v_{jGt}\}$$

Under the assumption that $v_{ij_g t}$ is independently identically distributed type 1 extreme values it is possible to obtain an analytic expression for the expectation of the maximum, which is particularly useful as it introduces smoothness into the estimation routine.

$$\delta_{ijt} = E\max\{\bar{\delta}_{ij_1t} + v_{j_1t}, ..., \bar{\delta}_{ijGt} + v_{jGt}\}$$
$$= \ln\left(\sum_g \exp(\bar{\delta}_{ij_gt})\right)$$

Apart from the re-definition of δ_{ijt} the DP problem remains similar to the model in the previous section. Calculation of purchase probabilities and market shares should be slightly modified to account for multiple tiers. Under the assumption that switching tiers within a given provider is costless and that consumers can observe v_{ij_gt} only after connection, the share of tier g conditional on choosing provider j can be obtained as in traditional static models.

$$\begin{aligned} s_{ij_gt|j} &= \Pr(\bar{\delta}_{ij_gt} + v_{ij_gt} \geq \bar{\delta}_{ij_kt} + v_{ij_kt}, \forall k \neq g|j) \\ &= \frac{\exp \bar{\delta}_{ij_gt}}{\sum_k \exp \bar{\delta}_{ij_kt}} \end{aligned}$$

Then predicted market shares for a consumer of type i are given by the expression below

$$\begin{aligned} s_{ij_gt} &= \sum_k s_{ikt-1} \Pr(j_g|a_t = j, a_{t-1} = k) \Pr(j|a_{t-1} = k) \\ &= \Pr(j_g|a_t = j) \sum_k s_{ikt-1} \Pr(j|a_{t-1} = k) \\ &= \frac{\exp \bar{\delta}_{ij_gt}}{\sum_k \exp \bar{\delta}_{ij_kt}} \sum_k s_{ikt-1} \frac{\exp V_i^{kj}}{\exp V_i^{k0} + \exp V_i^{kc} + \exp V_i^{ks}} \end{aligned}$$

where $j = \{0, c, s\}$ and g is the subscript for each tier offered by the provider j. Aggregate market shares are computed by integrating over the consumer types as before.

Mean utility flows for each tier are given by the solution to the system of simultaneous equations

$$\begin{cases} s_{c_g t} = \hat{s}_{c_g t}(\bar{\delta}_{c_1 t}, ..., \bar{\delta}_{c_{G_c} t}, \bar{\delta}_{s_1 t}, ..., \bar{\delta}_{s_{G_s} t}, \mathbf{\Theta}^n) \\ s_{s_g t} = \hat{s}_{s_g t}(\bar{\delta}_{c_1 t}, ..., \bar{\delta}_{c_{G_c} t}, \bar{\delta}_{s_1 t}, ..., \bar{\delta}_{s_{G_s} t}, \mathbf{\Theta}^n) \end{cases}$$

where $s_{c_g t}$ is the observed market share of tier; G_c and G_s are the total number of tiers offered by cable and satellite systems respectively; and $\hat{s}_{c_g t}(.)$ is the market share predicted by the model given vector of parameters $\mathbf{\Theta}^n$. Note that in the case of zero switching costs the model becomes a static nested logit model with uncertainty regarding within-provider tier-specific preferences in the second level of the nest. Let me now outline the benefits of using multi-tier data as some of them might not be obvious.

The gain in utilizing multi-product data is two-fold. First, there are simply more data that provide information for the identification of parameters and the model becomes more "realistic". Second, some structural parameters in the model can be identified without ever solving the consumer DP problem. In particular, data on movement between tiers of the same provider can be used to identify utility function parameters as was shown in Hendel and Nevo (2006). This is obvious from inspection of the probabilities conditional on choosing provider j above, which are functions of the tier-specific utility flows. One important conclusion from this discussion is that there is a simple solution for researchers whose research questions do not require estimating switching costs. Under a set of assumptions utility function parameters can be identified for the multi-product firm even in presence of significant firm-specific switching costs.

5.2 Caveats

There are several caveats in the model presented. Below I discuss only those that are specific to this study and omit discussion of the well-documented critique of the techniques I use to develop and estimate the model.

The most important potential problem is related to the definition of switching costs. In the present setup the switching cost is assumed to be an exogenous parameter known to consumers that is constant over time. This obviously is a very restrictive assumption. Clearly, DBS and cable systems are interested in controlling the size of the switching costs as it directly affects their optimal policies and resulting performance. It is conceivable that they have at least partial control over the parameter values. As discussed in the introduction, installation and equipment expenditures contribute to the size of the consumer switching costs. Recently, satellite systems have begun offering a variety of discount and rebate programs for their equipment. Sometimes the system offers free installation conditional upon choosing a particular programming package or specific terms of the agreement. Although in many cases this promotional activity reduces the upfront fee, it may simply transform the bulk of it into other types of switching costs, e.g. contractual lock-in. Besides, in order to get a discount offer a consumer might need to spend some time and effort to research the market. This might require to wait if there are no discounts currently available. It is also not clear what has happened to other components of switching costs. In any case, my personal communication with people who are cable or satellite subscribers reveals that most believe that switching costs today are significantly lower relative to their values in 1997. If switching costs indeed vary over time the model should definitely account for that. Regardless of whether we assume that consumers predict perfectly, or form some sort of expectations about future values of the switching cost parameters, the switching costs should enter state space of the consumer DP problem. At the moment, I leave this exercise as a topic for further research.

Another obvious problem is related to the modeling of multi-product providers by using a representative (most popular) tier. On the one hand, this is unavoidable in the case of the satellite data unless I can access this confidential information. Could the multi-tier data available for cable systems be useful in estimation when DBS data is not available? In general, aggregate data on consumer choices of various tiers conditional on choosing cable systems contains valuable information, which can be used to identify parameters of the utility function without ever solving the DP problem as discussed above. This, however, cannot help in identifying structural parameters of interest and is not going to help in reducing the computational burden because the parameters of the utility function are currently obtained in closed form, which is a very fast procedure. However, proper use of this information would definitely increase the efficiency of the estimates.

Construction of the local market market shares for satellite, which are not readily available, unavoidably introduces noise to the data on market shares. In the non-linear dynamic model described above, these errors in dependent variable are not as innocuous as they are in the linear case. Although I do not have a formal proof, it is very likely that even a nonsystematic error in satellite market shares will adversely affect the consistency of the estimates.

6 Data

Data for this paper was compiled from several sources. The most important source is Warren's cable factbooks. This source contains exhaustive information on cable systems for 1997-2006. Satellite data came from the internet.[12]

There are several issues to mention. First, cable data suffers from an enormous number of repeated values of observations, when the number of subscribers and other relevant information is not updated every year. Out of a total 11,973 systems available in the original data set, the number of systems that have updated information on the number of subscribers in at least 2 consecutive periods is 6,727. Given that satellite data is not available prior to 1997 the maximum possible length of time-series observations is 10. Frequency statistics for the number of observations in each year and the number of time runs is presented in the table 3.

There is an issue related to the timing of the sample. Most of the observations in the sample came from the early years. This is related to the problem of repeated values, which is particularly severe in later years. About

[12]I am grateful to my advisor Gregory Crawford and Ali Yurukoglu who generously shared their data with me.

Table 3: Timing structure of the sample data: number of systems, 1997-2006

Past obs.	End year 1998	1999	2000	2001	2002	2003	2004	2005	2006	Total
1	841	638	439	412	440	942	272	52	914	4950
2		438	223	86	80	107	127	3	26	1090
3			102	194	59	29	42	8	0	434
4				128	24	32	7	0	0	191
5					12	32	3	0	0	47
6						12	1	0	0	13
7							2	0	0	2
8								0	0	0
9									0	0
Total	841	1076	764	820	615	1154	454	63	940	6727

Source: own calculations

85 percent of the data points come from the 1997-2003 years. This feature of the data is directly related to one of the model's caveats, i.e. assuming that switching costs are constant over time. If switching costs vary over time, then their estimates should be considered as estimates relevant for the period 1997-2003 rather than for the later years.

Despite the fact that cable and satellite systems offer multiple tiers, I choose the most popular tier for each provider. For satellite it is Total Choice (DIRECTV). For cable it is either Basic, Expanded Basic 1 or Expanded Basic 2, depending on the number of subscribers.[13] The reason to throw away valuable information on tiers from the cable data is to treat cable and satellite symmetrically. There are two major DBS providers each offering multiple tiers. Ignoring this, while accounting for several products offered

[13] Almost in all cases whenever cable system offers more than one tier, the most popular tier is Expanded Basic 1 and in a few cases Expanded Basic 2. This choices are consistent with the official data from the FCC report 06-179, which states that by the end of 2004 about 96 percent of cable systems offered Expanded Basic tier and about 88 percent of subscribers purchased this tier.

by cable, would necessarily give incorrect predictions of the relative utility flows.

Another data issue is related to the definition of the relevant market. I define market as the area "passed" by the incumbent cable system. At the same time, satellite penetration rates are available only at the Designated Market Area (DMA) level. In order to compute satellite market share for each of the more narrowly defined markets I used an assumption similar to one in Chu (2007). Within a DMA satellite subscribers constitute a constant proportion of the non-cable subscribers. Define

$$R_{kt} = \frac{\#satsubs_{kt}}{M_{kt} - \#cabsubs_{kt}}$$

where k and t are DMA and time subscripts; $\#satsubs_{kt}$ is the number of satellite subscribers; M_{kt} is the total number of households; and $\#cabsubs_{kt}$ is the number of cable subscribers. Then satellite market share in market j located in DMA k is computed as

$$s_{jt}^{s} = (1 - s_{jt}^{c})R_{kt}$$

The rationale for this assumption is related to the timing of the entry by DBS. In the first place, satellite providers target areas where there is no alternative cable paid-television service or where the cable share is small. Therefore, one can expect that within the same DMA satellite penetration is relatively larger in the areas franchised to the cable systems with smaller market shares. Typically, satellite penetration is greater in rural and suburban than in the densely populated urban areas where cable companies have greater market shares.[14] Geographic variation in satellite penetration rates is supported by official statistics (see Section 3).

Another important question is the definition of the quality of programming content offered by a particular provider. Using number of channels offered as a proxy for quality of the system's programming may be problematic. In particular, such a proxy would not capture changes in the programming composition, holding the number of channels constant. In many cases, the data reveal that a lot of variation in the quality variable is due to the change in the composition of channels rather than due to change in the number of channels. In order to control for different compositions of channels I used data on the average cost of each channel charged by the television networks. Channels with unknown or zero costs were assigned a cost of $0.01.

Price data for cable and satellite services was adjusted using consumer price index with 1997 as the base year. Hence, any monetary equivalents computed in this paper are in 1997 prices.

General descriptive statistics of the data are presented in Table 4.

[14] Another reason to expect lower satellite penetration in urban areas is the necessity to locate receiver (dish) in a place that guarantees open access to the orbital satellite. In urban areas it was harder due to the presence of multistory buildings that may impede receiving satellite beams. Besides in multi-unit structures up until recently to install a dish a resident must obtain permission of the home owner, which was not always an easy task.

Table 4: Descriptive statistics for the key variables

variable	min	max	mean	med	sd
Quality(cable)	0.05	14.44	4.78	4.56	2.32
Quality(satellite)	4.49	14.88	8.60	9.60	3.31
Price(cable)	1.78	54.38	22.22	22.84	6.34
Price(satellite)	27.95	33.98	29.68	28.99	1.76
Market share (cable)	0.10	0.95	0.54	0.55	0.17
Market share (satellite)	0.01	0.68	0.16	0.14	0.10

Source: own calculations

7 Instruments and identification

7.1 Instruments

In order to identify parameters on endogenous variables, p and q, I used instruments that are similar to what is suggested by Crawford (2005). Below I provide arguments that support the validity of the instrumental variables.

Primary instruments for price and quality levels of cable providers are average prices and quality levels of other cable systems that belong to the same multiple-system-operator (MSO). These variables must be uncorrelated with the unobserved local market service characteristics, ξ, but should be reasonable proxies for the price and quality levels offered by the local cable system. Correlation in prices and quality levels across systems occurs because the owner of several cable systems typically negotiates programming fees and other contract arrangements with programming networks on behalf of all of its members simultaneously. In turn, correlation in the marginal costs of systems within the same MSO justifies correlation in their price and quality levels. For the instruments to be valid, one must ensure that the unobserved demand shocks, ξ's are not correlated across the systems. It is less obvious because MSO typically own geographically concentrated firms. If unobserved demand shocks are closely correlated across different cable markets, the validity of these instruments may be questionable.

The second set of instruments are cost shifters that affect prices and programming choice through differences in the bargaining power of the MSOs. Following the previous literature, I use the total number of homes passed and the number of subscribers served by the system's corporate parent as proxies for the bargaining power of the MSO. These variables stand for the differences in the MSO's bargaining power in the programming market, which in turn would affect costs and quality levels of the local operators. Another instrumental variable is the average capacity level of the systems within the MSO. Average capacity should be correlated with the ability of systems to get lower rates for bundles of programming networks offered by the same supplier. The total length of own coaxial lines of the local cable systems is a proxy for the differences in maintenance costs incurred by the systems in areas with different densities of houses.

The last set of instrumental variables was included to enhance identification of switching cost parameters. Switching costs are related to the importance of the past values of relevant variables for the current period choices. Hence, interactions of lagged values of the proper instrumental variables with current unobservables should generate moment conditions that identify switching costs. In this paper I used lagged values of all the instrumental variables discussed above.

7.2 Identification

Identification of the parameters of the dynamic model is a complex issue. In the context of my model there are two related identification issues to discuss. The first question relates to identification of switching costs parameters, while the second asks what identifies persistent consumer heterogeneity, as measured by the random coefficients.

Switching cost parameters define the importance of the past decisions (current states) for the current choices. In the model, current market share of a given service depends on the distribution of past market shares due only to the switching costs. Recall from equation (9),

$$\begin{aligned} s_{ct} &= f(\delta_{ct}, \delta_{st}, s_{ct-1}, s_{st-1}, \boldsymbol{\Theta}) \\ &= s_{ct-1} \Pr(c|c) + s_{st-1} \Pr(c|s) + (1 - s_{ct-1} - s_{st-1}) \Pr(c|0) \\ &= s_{ct-1}(\Pr(c|c) - \Pr(c|0)) + s_{st-1}(\Pr(c|s) - \Pr(c|0)) + \Pr(c|0) \end{aligned}$$

where $Pr(j|k)$ is a shortcut for the probability of choosing alternative j in state k. When the switching costs are zeros, $\Pr(c|s) = \Pr(c|c) = \Pr(c|0) = \Pr(c)$, and past choice (current state) is irrelevant for the optimal consumer decision. Hence, the current market share becomes simply a logistic probability of choosing cable in the current period. From the expression above, it is clear that identification of switching costs is based on the consumer "arrival pattern", i.e. whether current consumers are drawn disproportionally more from outside share than from the rival's share.

For positive values of the satellite switching cost parameter, $\Pr(c|0) >$

$\Pr(c|s)$ and $\Pr(s|0) > \Pr(s|c)$.[15] Intuitively, a satellite subscriber attains higher value from the current service than for the outside alternative. This holds by definition, as disconnection is costless. In order to rationalize the switch to cable, the difference between the cable value and current value should offset switching costs. Hence, the probability of switching to cable for a current satellite subscriber of type i is lower than the probability of cable choice for the same type in outside state. Since the value function from satellite service does not directly depend on satellite switching costs, increases in the satellite switching costs would reduce the relative attractiveness of the outside alternative, which directly depends on the satellite switching cost. This reduction further widens the gap between probabilities of choosing cable in outside versus satellite state.

A heuristic argument for the use of lagged instrumental variables for identification of switching costs is based on a non-parametric idea of identifying state dependence. Intuitively, if the coefficients on the past states in a reduced form regression of current cable market share on the lagged market shares (instrumented using lagged exogenous regressors) and a set of contemporaneous exogenous regressors are statistically significant than there is state dependence. In a reduced form specification coefficients on lagged cable and satellite shares are 0.634 (s.e. 0.049) and 0.177 (s.e. 0.042) respectively.

Identification of random coefficient parameters relies on the variation in the choice sets across markets and over time. There is no variation in the set of available products because there are always two alternatives and an

[15] Note that the difference between the probabilities is strictly increasing in switching cost of the alternative we condition on.

outside option. However, the data includes a number of cross-sectional observations with significant variation in observed quality and prices across markets. Unfortunately, as it is typical for models that rely only on aggregate data, identification of consumer heterogeneity may be weak, particularly for the case when the set of products is small.

8 Results

I estimated several demand side models. Table 5 presents results of the estimation for static, myopic, and dynamic models. The static model (without random coefficients) is a simple logit specification with switching cost parameters restricted to zero. The myopic model allows for non-zero switching cost parameters but sets the discount factor to zero. The dynamic model estimates switching cost parameters under the assumption that the discount factor is 0.95. In addition, I estimated both the static and dynamic models with random coefficients.

The results from the static OLS and IV regressions suggest that instruments have considerable effect on the parameter estimates. In a single variable regression, the bias of the OLS coefficient estimate is defined by the covariance between the regressor and the unobserved error term. If one is willing to apply this shortcut to a multivariable regression, then the difference between the estimates from the OLS and IV specifications is consistent with positive covariance between price and the unobserved quality component, ξ_{jt}, and negative covariance between observed and unobserved quality.

The estimates of switching cost parameters produced by myopic and dy-

Table 5: Estimation results

Variable	OLS	IV, GMM					
		One-type			R.C. model		
		Stat1	Myop1	Dyn1	Stat2	Dyn2	Dyn3
const	1.110*	1.648*	1.382*	1.194*	1.556*	1.130*	1.125*
	(0.019)	(0.056)	(0.059)	(0.092)	(0.165)	(0.151)	(0.136)
sat.dum.	-1.678*	-1.821*	-0.955*	-1.127*	-1.833*	-1.124*	-1.121
	(0.011)	(0.020)	(0.224)	(0.083)	(0.052)	(0.234)	(0.725)
time	-0.061*	-0.139*	-0.117	-0.083*	-0.119*	-0.091*	-0.091*
	(0.002)	(0.006)	(0.008)	(0.008)	(0.015)	(0.009)	(0.011)
q (qual.)	0.194*	0.290*	0.258*	0.204*	0.273*	0.207*	0.207*
	(0.002)	(0.007)	(0.010)	(0.011)	(0.013)	(0.016)	(0.021)
p (price)	-0.052*	-0.083*	-0.076*	-0.056*	-0.072*	-0.054*	-0.054*
	(0.001)	(0.003)	(0.005)	(0.004)	(0.009)	(0.006)	(0.008)
Switching costs							
η_c (cable)			-0.389	0.507*		0.477*	0.475
			(0.273)	(0.171)		(0.194)	(0.307)
η_s (satellite)			0.709*	0.869*		0.942*	0.944*
			(0.179)	(0.118)		(0.400)	(0.463)
Standard deviations							
const					0.773	0.088	0.102
					(0.649)	(2.328)	(2.829)
sat.dummy					0.010		0.014
					(4.299)		(6.783)
price					0.025		
					(0.019)		

*Standard errors in parentheses: * significant at 5%, ** at 10% level*

namic models of consumer behavior are quite different. The point estimate of cable switching costs from the myopic specification is negative and not statistically significantly different from zero. Meanwhile the estimate of satellite switching costs is statistically significant and has a positive sign. In the model that accounts for the forward-looking consumer behavior both estimates of switching costs are positive and statistically significant. One possible explanation of the negative point estimate of cable switching costs in the myopic model is that smooth changes in the cable shares are incorrectly interpreted as high turnover of consumers when it pays to become a new customer, while keeping the product in the next period is less attractive than the outside or satellite alternative. In case of forward-looking behavior, consumers may rationally choose to stay with the cable system even when it generates less attractive flow utility in the current period. This would be optimal if expectations of the future utility flow are bright enough and it is costly to make repeated connections.

To evaluate the economic significance of the parameter estimates, I use the estimate of the marginal disutility from the monthly fee to transform the utility measure of switching costs into their monetary equivalents. For cable systems the switching cost is approximately $109, while for satellite the costs are about $186 in 1997 prices.

Do these numbers make sense? First, when comparing cable and satellite switching costs with each other, the difference is consistent with expectations because at least the explicit (up-front connection fees) component of switching costs is typically higher for DBS providers. As to the absolute monetary values, it is hard to tell because a considerable part of the switching costs may be generated by unobserved hassle utility costs. In order to isolate pure implicit utility costs, one can use data on average explicit connection fees. For example, the direct cost of the professional installation of cable service in 1997 was about $40 (FCC Report on cable industry prices, December 15, 1997). This does not include equipment cost, which was typically rented rather than purchased by subscribers. Additional fees in terms of extra equipment and installation fees may be required for extra television sets in the same household. Warren's data contain information on the installation fees for some of the cable systems. In 1997 these numbers average about $37 (fees vary considerably across systems and tiers). After accounting for direct fees, there still remain hassle costs of about $60 to $70 in implicit switching costs for cable.

As for satellite, the equipment and professional installation fees were considerably larger. The official professional installation fee was about $150 not including equipment. The equipment cost ranged from $100 to $300 depending on the configuration and the number of television sets in the same household.[16] Satellite equipment was usually purchased by the subscribers rather than rented (except in a few cases). Therefore, a consumer who decides to disconnect or switch to an alternative provider may be able to resell equipment in the secondary market. This however would imply spending extra effort and losses in the equipment value relative to its initial price.

Another way of looking at monetary values of switching costs is to compare them to the annualized monthly fees. In 1997, the average monthly fee for the most popular cable tier was about $28 and $30 for satellite. On an annual basis consumers paid about $336 for cable and $360 for satellite in 1997 prices. Then estimated switching cost constitute about 32 and 52 percent of the annual expenditures on the cable and satellite service respectively.

The estimate of the coefficient on the linearized time trend suggests that

[16]DBS providers recognized that equipment and installation costs are among major impediments in attracting new customers. This resulted in a number of various discount schemes like one offered by EchoStar in terms of $50 professional installation fee and discounts for the second dish. In many cases a consumer can purchase a $50 do-it-yourself installation kit and purchase equipment in a secondary market or from discount stores for less.

the average utility from paid television services was gradually decreasing over time. This is evidence that the outside alternative wos improving. In particular, the development of video rental services (e.g. BlockBuster, Hollywood Video, Netflix, etc.) and considerable improvements in the accessibility and quality of the video recording technologies increased the relative attractiveness of the option of not having paid television.

The negative coefficient on satellite dummy implies that satellite television service generated lower average utility relative to the cable alternative. One possible explanation is related to the supplementary services offered by cable companies. This difference may also reflect the ability of cable systems to broadcast local channels, while DBS providers gained this opportunity only recently.

Coefficients on quality and price variables have the expected signs and are statistically significant in all specifications. One way to assess the economic significance of the coefficients is to compute implied price and quality elasticities. It is worth noting that in a dynamic framework the definition of price elasticity is more complicated than in static models. In particular, the value of a price elasticity depends on whether the price change is anticipated and whether it is permanent. I use two definitions of price elasticity in a dynamic model. Let E^S denote the static own-price elasticity. Let E^D_{SR} denote the short-run elasticity from a dynamic model assuming an unanticipated non-permanent increase in the monthly subscription fee. Let E^D_{LR} stand for the long-run elasticity from a dynamic model assuming an unanticipated permanent increase in monthly subscription fee. Then the relevant formulas for the price elasticities of provider j are

$$
\begin{aligned}
E_j^S &= \frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = \alpha_2(1-s_j)p_j \\
E_{SR,j}^D &= \frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = \alpha_2(1-s_j)p_j \\
E_{LR,j}^D &= \frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = \alpha_2\left(s_0\left(\frac{\partial V^{jj}}{\partial \delta_j} - \frac{\partial V^{00}}{\partial \delta_j}\right) + s_k\left(\frac{\partial V^{jj}}{\partial \delta_j} - \frac{\partial V^{kk}}{\partial \delta_j}\right)\right)p_j
\end{aligned}
$$

where $k \neq j; k, j \in \{c, s\}$. Quality elasticities can be obtained similarly. Table 6 lists price and quality elasticities.

Table 6: Price and quality elasticities from dynamic and static models

	Cable		Satellite	
	Price	Quality	Price	Quality
Static	-1.07	0.64	-2.10	2.10
Dynamic short-run (D3)	-0.72	0.45	-1.41	1.47
Dynamic long-run (D3)	-0.84	0.52	-1.67	1.75

Short-run price and quality elasticities from the static model are significantly larger than short- and long-run elasticities from the dynamic model. These findings are consistent with the theoretical prediction that switching costs make consumer demand less elastic. It is worth noting that previous studies of the television market estimate elasticities for specific tiers, while in this paper I use price and quality data from the most popular tier and evaluate elasticity at the total cable share. Therefore, I expect that my estimates of price elasticity from the static model should be lower in absolute value relative to the previous findings. For instance, Crawford (2000) finds that own price elasticity for basic and expanded basic services are -1.67 and -0.66 respectively, while Goolsbee and Petrin (2004) estimated the elasticity of expanded basic to be -1.53.

In the static model, standard deviations on the constants and price coefficient are not statistically significant. In the dynamic model, standard deviations on constant and satellite dummy are not statistically significant.

9 Counterfactual simulations

In this section, I present a simple representative consumer supply side framework, which is used to simulate counterfactual scenarios of paid television industry evolution. In particular, I evaluate the effect of DBS entry on the optimal cable policy (case "No satellite, switching costs"). Another scenario considers the case of a cable monopoly where consumer switching costs are completely subsidized (case "No satellite, no switching costs").[17] A third possible scenario, when both cable and satellite switching costs are completely subsidized (i.e. static demand with duopoly competition on supply side) requires more complex model and is left as a topic for further research.

Simulating counterfactual experiments requires knowledge of the supply-side parameters. In order to estimate the cost structure of the cable carriers I make a set of simplifying assumptions. First, I assume that all factors that affect costs and unobserved service characteristics, ξ_{ct}, of cable providers would remain the same under the counterfactual scenario of no DBS and a complete elimination of switching costs.[18] The meaning of the assumption is

[17]For example, in case of government regulation that requires cable companies to charge their customers only on the pay-per-view basis.

[18]This is obviously a strong assumption as many of the "cost shifters" employed in the demand model estimation might be affected by the strategic actions of cable providers in response to the entry by DBS, e.g. change in ownership structure.

that the model provides a partial equilibrium analysis by ignoring the overall effect of satellite entry on the relevant market variables. Second, consistent with the current specification of the demand side model, I maintain the linearity assumption on the consumer utility from television service. Third, I assume that the total cost function of cable providers is perfectly scalable in the number of subscribers, i.e. the marginal cost of providing service to any number of subscribers is constant. Finally, I use a one-consumer-type version of the demand side model. Under these assumptions, optimal quality choice of cable firms would not be affected by the DBS entry or by the elimination of the consumer switching costs.[19] Below I present a more formal discussion of the supply-side model.

Throughout this section I assume a representative consumer model; therefore, the subscript i is omitted. Consistent with the demand side model, I maintain an assumption that consumers attain per-period utility from consuming television service denoted by

$$\delta_{jt} = \delta(q_{jt}, p_{jt}, \xi_{jt}), j = c, s \tag{18}$$

with the flow utility from the outside alternative normalized to zero. As before, consumers are assumed to forecast future flow utility using information on the current pair of utility levels only. According to the assumptions of the demand-side model, consumer state variables include only overall flow utility and not price, observed and unobserved quality separately. This implies

[19] Even though some previous studies, e.g. Goolsbee and Petrin (2004), Chu (2007), find that satellite entry has an effect on the optimal cable quality choice, the set of assumptions above secures a clean outcome where the entire effect of satellite entry and switching costs would be reflected by the change in the optimal cable price only.

that any combinations of q_{jt}, p_{jt}, and ξ_{jt} that result in the same flow utility would be viewed by the consumer as equally attractive. The model does not differentiate between high-quality expensive and low-quality low-price programming offer as long as both generate the same δ_{jt}.

The consumers' policy choices result in aggregate market shares, which are functions of the current level of utility generated by cable provider, δ_{ct}, last period market shares, s_{ct-1}, s_{st-1} (which define current consumer's state), and current choice of the consumer flow utility by satellite provider, δ_{st}.

Each period cable firm collects revenue equal to the monthly subscription fee times the number of subscribers, i.e. $p_{ct}Ms(p_{ct}, q_{ct}, \cdot)$, where M denotes market size and is assumed to be constant over time. Providing quality, q_{ct}, is costly. Let $C(q_{ct}, X_{ct}, \xi_{ct}, Ms_{ct})$ denote the producer total cost function of providing quality level q_{ct} to Ms_{ct} subscribers in the market. The cost function is allowed to depend on a vector of "cost shifters", X_{ct}, as well as on the current realization of exogenous "unobserved" service characteristics, ξ_{ct}. Then the producer per-period payoff (profit) function is defined as

$$\pi(p_{ct}, q_{ct}, \delta_{st}, \xi_{ct}, X_{ct}, s_{ct-1}, s_{st-1}) = \\ Ms(p_{ct}, q_{ct}, \delta_{st}, \xi_{ct}, s_{ct-1}, s_{st-1})p_{ct} - C(q_{ct}, X_{ct}, \xi_{ct}, Ms(\cdot)) \qquad (19)$$

In the beginning of each period, the producer observes the current value of the "unobserved" (by us) product characteristics, ξ_{ct}, current period satellite flow utility, δ_{st}, and realizations of the exogenous cost shifters, X_{ct}. Hence, in the beginning of the period the producer has complete information about the current period profit function for any feasible policy choices of $\{p_{ct}, q_{ct}\}$.

Evolution of the exogenous variables δ_{st}, ξ_{ct}, and X_{ct} is perceived by the producer as a stochastic process known up to a parameter vector. Current market shares are deterministic functions of quality (both observed and unobserved), price, and past market shares

$$s_{ct} = s_{ct-1}\Pr(c|c) + s_{st-1}\Pr(c|s) + (1 - s_{ct-1} - s_{st-1})\Pr(c|0)$$

$$s_{st} = s_{st-1}\Pr(s|s) + s_{ct-1}\Pr(s|c) + (1 - s_{ct-1} - s_{st-1})\Pr(s|0)$$

where $\Pr(j|k)$ is a shortcut for $\Pr(a_t = j|a_{t-1} = k), k, j = c, s$, with a_t and a_{t-1} denoting consumer current choice and state respectively.

I proceed under the following set of assumptions:

Assumption 2: Consumer flow utility is linear in the price and quality variables

$$\delta_{ct} = \alpha_{0c} + \alpha_{c1}q_{ct} + \alpha_{c2}p_{ct} + \xi_{ct}. \tag{20}$$

Assumption 3: The total cost function is perfectly scalable in the number of subscribers

$$C(q_{ct}, X_{ct}, Ms_{ct}) = Ms_{ct}C(q_{ct}, X_{ct}). \tag{21}$$

Assumption 4: The change in market structure due to entry of DBS and/or elimination of consumer switching costs does not affect any of the cost shifters, X_{ct}, and unobserved product characteristics, ξ_{ct}

Suppose that the producer maximizes expected present discounted value of future cash flows over an infinite horizon. Then the producer problem is

$$\max_{p_{ct},q_{ct}} \sum_{t=0}^{\infty} \beta^t E[\pi(p_{ct}, q_{ct}, \delta_{st}, \xi_{ct}, X_{ct}, \cdot)]. \tag{22}$$

The expectation is taken with respect to the distribution of future values of the exogenous random variables, $(\delta_{st}, \xi_{ct}, X_{ct})$

From Assumption 2, $\delta(q_{ct}, p_{ct}, \xi_{ct})$ is a strictly decreasing function in p_{ct}. Therefore, there exists a well-defined inverse function

$$p = \delta^{-1}(\delta_{ct}, q_{ct}, \xi_{ct}). \tag{23}$$

Moreover, $\frac{\partial \delta^{-1}(\delta_{ct}, q_{ct}, \xi_{ct})}{\partial q_{ct}}$ is constant.

Let producer choice variables be defined as (δ_{ct}, q_{ct}) instead of (p_{ct}, q_{ct}). Then the producer maximization problem can be expressed as

$$\max_{\delta_{ct},q_{ct}} \sum_{t=0}^{\infty} \beta^t E[\pi(\delta_{ct}, q_{ct}, \delta_{st}, \xi_{ct}, X_{ct}, \cdot)], \tag{24}$$

which can also be written as a conventional Bellman equation

$$W(s_{ct-1}, s_{st-1}, \delta_{st}, \xi_{ct}, X_{ct}) =$$

$$\max_{\delta_{ct},q_{ct}} \left\{ \begin{array}{l} s(s_{ct-1}, s_{st-1}, \delta_{st}, \delta_{ct})(\delta^{-1}(\delta_{ct}, q_{ct}, \xi_{ct}) - C(q_{ct}, \xi_{ct}, X_{ct}) + \\ \beta E[W(s_{ct}, s_{st}, \delta_{st+1}, \xi_{ct+1}, X_{ct+1}) | \delta_{ct}, q_{ct}, s_{ct-1}, s_{st-1}, \delta_{st}, \xi_{ct}, X_{ct}] \end{array} \right\}$$

Note that conditional on policy choice, δ_{ct}, the choice of quality, q_{ct}, does not have any dynamic implications.

From the first order conditions for optimal quality choice,

$$FOC[q_{ct}] : \frac{\partial \delta^{-1}(\delta_{ct}, q_{ct}, \xi_{ct})}{\partial q_{ct}} - \frac{\partial C(q_{ct}, \xi_{ct}, X_{ct})}{\partial q_{ct}} = 0 \tag{25}$$

it is clear that $q^*_{ct} = q(\xi_{ct}, X_{ct})$ does not depend on the optimal choice of a dynamic control. The first term is constant due to the linearity of the utility function. Then I can write the producer dynamic programming problem in terms of a Bellman equation that is partially maximized with respect to q_{ct}.

$$W(s_{ct-1}, s_{st-1}, \delta_{st}, \xi_{ct}, X_{ct}) =$$
$$\max_{\delta_{ct}} \left\{ \begin{array}{l} s(s_{ct-1}, s_{st-1}, \delta_{st}, \delta_{ct})(\frac{1}{\alpha_2}(\delta_{ct} - \alpha_0 - \alpha_1 q^*(\xi_{ct}, X_{ct}) - \xi_{ct} - \alpha_2 \tilde{C}(\xi_{ct}, X_{ct}))+ \\ \beta E[W(s_{ct}, s_{st}, \delta_{st+1}, \xi_{ct+1}, X_{ct+1}) | \delta_{ct}, s_{ct-1}, s_{st-1}, \delta_{st}, \xi_{ct}, X_{ct}] \end{array} \right\}$$

Let

$$H(\xi_{ct}, X_{ct}) \hat{=} \frac{1}{\alpha_2}(-\alpha_0 - \alpha_1 q^*(\xi_{ct}, X_{ct}) - \xi_{ct} - \alpha_2 \tilde{C}(\xi_{ct}, X_{ct})) \tag{26}$$

Then

$$W(s_{ct-1}, s_{st-1}, \delta_{st}, \xi_{ct}, X_{ct}) =$$
$$\max_{\delta_{ct}} \left\{ \begin{array}{l} s(s_{ct-1}, s_{st-1}, \delta_{st}, \delta_{ct})(\frac{\delta_{ct}}{\alpha_2} + H(\xi_{ct}, X_{ct}) \\ \beta E[W(s_{ct}, s_{st}, \delta_{st+1}, \xi_{ct+1}, X_{ct+1}) | \delta_{ct}, s_{ct-1}, s_{st-1}, \delta_{st}, \xi_{ct}, X_{ct}] \end{array} \right\}$$

In order to reduce the dimensionality of the state space, I make another major simplifying assumption

Assumption 5: The producer perceives the current period value of function

$H(\xi_{ct}, X_{ct})$ as a sufficient statistic for the distribution over its future values.

$$P(H_{ct+1}|\xi_{ct}, X_{ct}, H_{ct}) = P(H_{ct+1}|H_{ct}) \tag{27}$$

Obviously, this assumption is very strong. In particular, I bypass an explicit transformation of a vector of several random variables, ξ_{ct} and X_{ct}, each having unknown distribution, via relationship (25) into a scalar random variable by directly assuming its distribution $P(H_{ct+1}|H_{ct})$. However, this assumption reduces the producer state space considerably, which makes it feasible to numerically solve the DP problem. In practice, I solve the following modified producer Bellman equation

$$W(s_{ct-1}, s_{st-1}, \delta_{st}, H_{ct}) =$$
$$\max_{\delta_{ct}} \left\{ \begin{array}{l} s(s_{ct-1}, s_{st-1}, \delta_{st}, \delta_{ct})(H_{ct} - \delta_{ct}) + \\ \beta E[W(s_{ct}, s_{st}, \delta_{st+1}, H_{ct+1})|\delta_{ct}, s_{ct-1}, s_{st-1}, \delta_{st}, H_{ct}] \end{array} \right\}$$

Note that by Assumption 4, values of $H(\xi_{ct}, X_{ct})$ will be constant across various scenarios. Therefore, I can solve for H_{ct} at a finite number of points in the producer state space to recover a sequence of numbers, $\{H_{ct}\}_{t=0,\dots,T}$ that rationalizes the sequence of optimal policy choices, $\{\delta_{ct}\}_{t=0,\dots,T}$, observed in the data. This can be done by first solving for the optimal producer policy $\delta_{ct} = \delta(s_{ct-1}, s_{st-1}, \delta_{st}, H_{ct})$ and then "inverting-out" H_{ct} values by matching model predictions to the actual data.[20]

[20]For a specific transition process on H_{ct} assumed below it can be shown that the optimal policy is strictly monotone in H_{ct}

The solution algorithm is iterative and consists of several steps. First, I specify an empirical version of the evolution of state variable H_{ct} by assuming that producer beliefs fit into

$$H_{ct+1} = a_0 + a_1 H_{ct} + \sigma_H \omega_{ct+1}, \tag{28}$$

where ω_{ct+1} is a next period innovation that is independently identically distributed as $N(0,1)$. Second, I use the final estimates of the transition parameters for δ_{st} from the demand side model. Third, I guess initial values for a_0, a_1, and σ_H. Then I use a three-step iterative procedure of (1) solving for the producer optimal policy at a finite number of grid points in the state space; (2) "inverting-out" a set of H_{ct} values by matching the observed policy δ_{ct} to the predicted one in the previous step; and (3) updating transition parameters a_0, a_1, σ_H. The iterations are repeated until complete convergence on both the producer value function and the resulting optimal policy. Recovered H_{ct} values in each market provide enough information to simulate two counterfactual scenarios.

For the first scenario, when there is no DBS but there are consumer switching costs (entry costs), I redefine the consumer and producer DP problems (to account for no DBS in the market) and solve them iteratively by updating consumer beliefs in equation (8) after solving for the optimal producer policy in any given iteration. A new sequence of δ_{ct} in each market is obtained when complete convergence on (1) consumer DP problem, (2) producer DP problem, and (3) optimal producer policy choice is reached.

For the second scenario, in the absence of the DBS and no switching costs, I (numerically) solve a static problem with market shares given by logit probabilities.

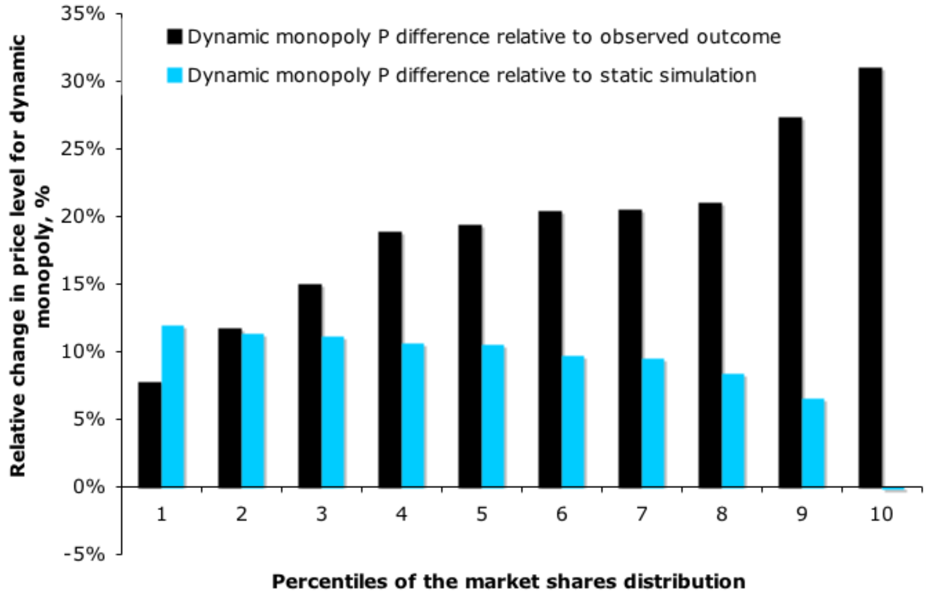
9.1 Simulation results

Elimination of DBS from the market would on average result in an increase in cable price by 19.23% (median 16.03%) relative to the observed outcome. Elimination of DBS combined with a subsidization of consumer switching costs in a static monopoly scenario would cause on average a 31.09% (median 27.71%) increase in cable prices. Given that the demand side model suggests a low elasticity of demand for television service, one could expect a considerable price change if paid television service was monopolized.

The average price increase in the static monopoly environment exceeds the one in case of cable monopoly with consumer switching costs (henceforth, dynamic monopoly). This seems reasonable given that with significant entry costs consumers would "demand" larger disounts in the monthly fee to connect to a service provider. According to theoretical literature on switching costs, firms face a tradeoff between incentives to invest into customer base by offering discounts and to capitalize on existing market shares by charging higher price. It is conceivable that investment incentive is significantly larger than capitalization incentive for the firms with smaller market shares. To explore this possibility, I compare the dynamic monopoly pricing scheme to prices under a static monopoly and to the actual observed prices.

Figure 3 suggests that cable firms in the lower 10th percentile of the market shares distribution charge prices that are fairly close to the observed

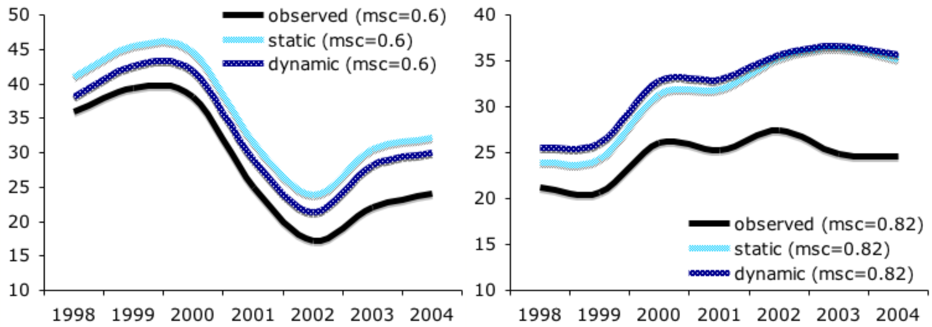
Figure 3: Dynamic monopoly price relative to the observed outcome and static counterfactual across 10 percentiles of market shares distribution



prices and are the most different from static monopoly optima. Black bars can be viewed as a hypothetical increase in price for a set of firms within a given percentile of the market shares distribution if DBS is eliminated from the market. With the increase in the market share, the incentive to capitalize on the existing consumer base increases and the investment in new customers becomes less important. Light-colored bars could be interpreted as price discounts (relative to the static monopoly optima) for various firm sizes due to dynamic considerations. Figure 3 provides evidence supporting the idea that cable firms with low shares offer considerable price discounts to attract new consumers. The largest firms set optimal dynamic monopoly prices higher than their optimal static monopoly price.

Similar observation could be made by inspecting counterfactual scenarios of price evolution for two firms: a typical firm with a market share of about

Figure 4: Evolution of optimal static and dynamic monopoly prices in 1998-2004 for two firms



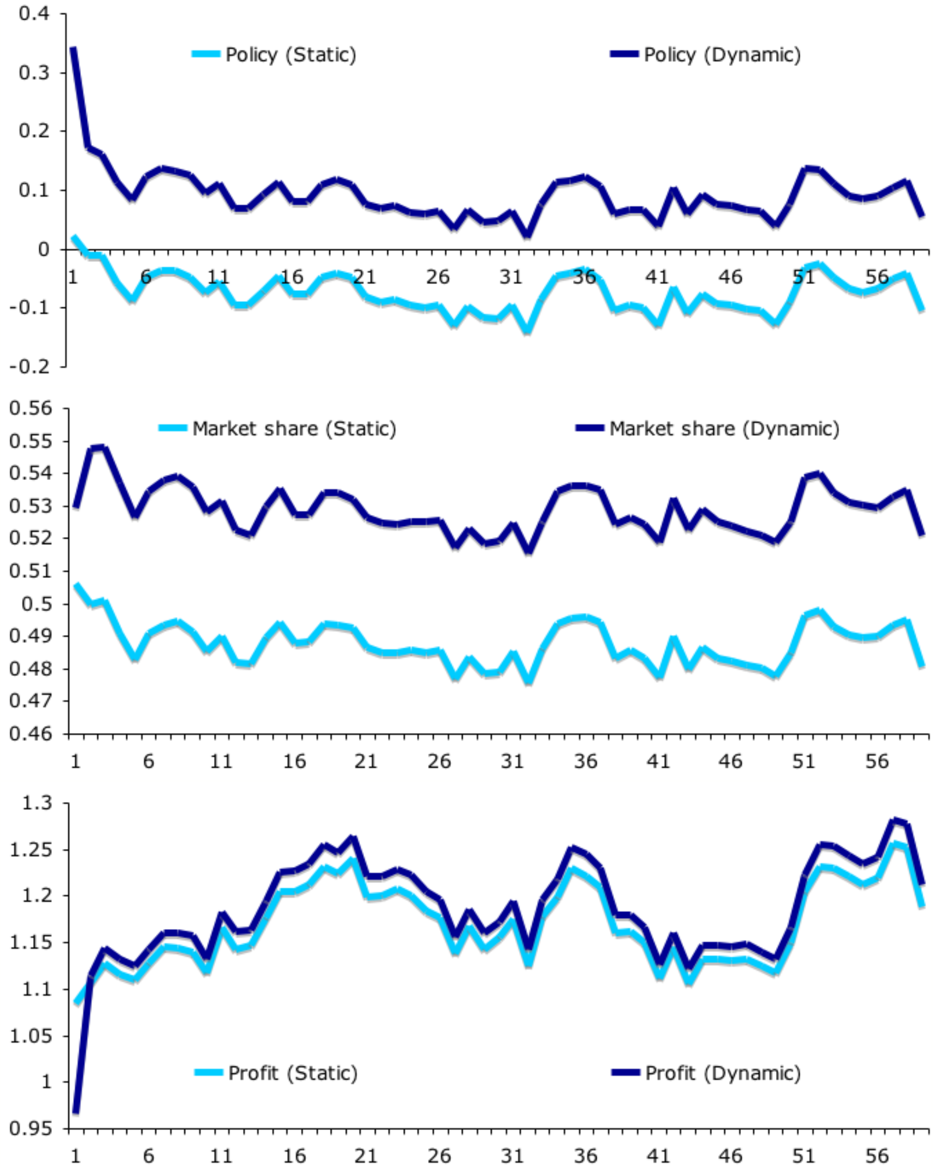
0.6 and a firm with significant market share of 0.82.

Figure 4 describes evolution of prices across time for two firms. A firm with a 0.6 market share demonstrates a pricing pattern similar to the average in the industry. Interestingly, a firm with an 0.82 market share suggests a significantly different path, where the dynamic optimal price is higher than the static monopoly optimum.

In order to further explore the difference between static and dynamic monopoly pricing I conducted another simulation experiment. In particular, I simulated 60 periods of industry evolution in 30 distinct markets assuming a mean value of H-function as initial condition for cost structure in each market and zero intial market share. For every next period and for each market, I draw a random innovation to the H-function according to the supply-side estimates. Then I update optimal producer choice and the consequent realization of the market share. Then the data on the optimal producer policy choice, δ_{cmt}, resulting market share, s_{cmt}, and normalized producer profit is averaged across markets for each time period.

Figure 5 describes the evolution of the variables across 60 simulated pe-

Figure 5: Average evolution of δ_{ct}, s_{ct} and cable profits for 30 simulated markets over 60 time periods



riods. Note that the first chart describes optimal δ_{ct} choices where higher values of δ_{ct} correspond to lower prices. Even though the optimal dynamic monopoly price is everywhere lower than the optimal static price, the market share and the resulting profit is everywhere higher for the dynamic monopoly.

10 Conclusions

This paper develops and estimates a dynamic model of consumer choice in the paid television industry. The proposed framework nests a static discrete choice model as a special case and, hence, allows for direct testing of the research hypothesis about significant switching costs in the industry. I use data from the U.S. television market to estimate structural parameters of the model. The estimates strongly support the existence of significant, both in statistical and economic sense, switching costs. In particular, the monetary value of switching cost for cable and DBS systems are \$109 and \$186 (in 1997 prices) respectively. These estimates are roughly 32 percent and 52 percent of the annual cable and satellite bills respectively.

According to the results, the static model overestimates the elasticities of demand with respect to price and quality. The static price elasticity estimate is -1.07, while the dynamic model estimates short- and long-run elasticity of -0.72 and -0.84 respectively. The myopic model offers lower switching cost parameters and, similar to static model, more elastic price and quality elasticities.

In order to evaluate the effect of DBS entry on the optimal cable policy, I suggested a simple supply side model. Assuming that satellite policy and the evolution of the cable carriers' cost structure is exogenous, I use an iterative nested fixed-point algorithm to solve for the optimal producer policy and recover the underlying costs structure that rationalizes observed policy choices. Under the assumption that the change in market structure does not affect any of the relevant exogenous variables, I simulate two counterfactual scenarios. According to the estimates, satellite entry will have a considerable effect on cable prices. In particular, in the absence of DBS cable prices would be on average 19 percent higher (median increase of 16%) relative to the observed outcome. If there is no DBS competition and the switching costs are subsidized, then the static monopoly price would likely be on average 31 percent (median 28%) higher than the observed cable prices.

References

Ackerberg, D. (2003). Advertising, learning, and consumer choice in experience good markets: an empirical examination. *International Economic Review*, 44:1007–1040.

Berry, S. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, 25:242–262.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63:841–890.

Borenstein, S. (1992). The evolution of u.s. airline competition. *The Journal of Economic Perspectives*, 6:45–73.

Carranza, J. E. (2006). Consumer heterogeneity, demand for durable goods and the dynamics of quality. Meeting Papers 247, Society for Economic Dynamics.

Chu, C. S. (2007). The effect of satellite entry on product quality for cable. Unpublished dissertation, Stanford University.

Crawford, G. S. (2000). The impact of the 1992 cable act on household demand and welfare. *RAND Journal of Economics*, 31:442–449.

Crawford, G. S. (2005). The discriminatory incentives to bundle in the cable television industry. Mimeo, University of Arizona.

Crawford, G. S. and Shum, M. (2005). Uncertainty and learning in pharmaceutical demand. *Econometrica*, 73(4):1137–1173.

Crawford, G. S. and Shum, M. (2007). Monopoly quality degradation and regulation in cable television. *Journal of Law and Economics*, 50:181–219.

Erdem, T. and Keane, M. (1996). Decision-making under uncertainty: capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science*, 15:1–20.

Erdem, T., Keane, M., Oncu, S., and Strebel, J. (2005). Learning about computers: an analysis of information search and technology choice. *Quantitative Marketing and Economics*, 3:207–246.

Farrell, J. and Klemperer, P. (2007). Coordination and lock-in: competition with switching costs and network effects. *Handbook of Industrial Organization. Chapter 31.*, 3:1967–2072. Edited by M. Armstrong and R. Porter.

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

Gordon, B. (2006). A dynamic model of consumer replacement cycles in the pc processor industry. Unpublished manuscript, Carnegie Mellon University.

Gowrisankaran, G. and Rysman, M. (2007). Dynamics of consumer demand for new durable goods. Unpublished manuscript, University of Arizona.

Hartmann, W. and Viard, B. (2006). Do frequency reward programs create switching costs. Research Paper 1941, Standford Graduate School of Business.

Hendel, I. and Nevo, A. (2006). Measuring the implications of sales and consumer inventory behavior. *Econometrica*, 74:1637–1673.

Israel, M. (2003). Consumer learning about established firms: evidence from automobile insurance. Working Paper 0020, The Center for the Study of Industrial Organization at Northwestern University.

Kim, J. (2006). Consumers' dynamic switching decisions in the cellular service industry. Working Paper 06-24, The Networks, Electronic Commerce, and Telecommunications Institute.

Kim, M., Kliger, D., and Vale, B. (2003). Estimating switching costs: the case of banking. *Journal of Financial Intermediation*, 12:25–56.

Kiser, E. (2002). Predicting household switching behavior and switching costs at depository institutions. *Review of Industrial Organization*, 20:349–365.

Klemperer, P. (1987a). The competitiveness of markets with switching costs. *RAND Journal of Economics*, 18:138–150.

Klemperer, P. (1987b). Markets with consumer switching costs. *The Quarterly Journal of Economics*, 102:375–394.

Klemperer, P. (1995). Competition when consumers have switching costs: an overview with applications to industrial organization, macroeconomics, and international trade. *The Review of Economic Studies*, 62:515–539.

Knittel, C. (1997). Interstate long distance rates: search costs, switching costs and market power. *Review of Industrial Organization*, 12:519–536.

Melnikov, O. (2001). Demand for differentiated durable products: the case of the U.S. computer printer market. Unpublished manuscript, Cornell University.

Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica*, 55:999–1033.

Salies, E. (2005). A measure of switching costs in the GB electricity retail market. Working Paper 2005-9, GRJM.

Sharpe, S. (1997). The effect of consumer switching costs on prices: a theory and its application to the bank deposit market. *Review of Industrial Organization*, 12:79–94.

Shy, O. (2002). A quick-and-easy method for estimating switching costs. *International Journal of Industrial Organization*, 20:71–87.

Sturluson, J. (2002). *Consumer search and switching costs in electricity retailing*. Ph.D. thesis, Chapter 1, in Topics in the Industrial Organization of Electricity Markets, Stockholm School of Economics, Sweden.

Wise, A. and Duwadi, K. (2005). Competition between cable television and direct broadcast satellite: the importance of switching costs and regional sports networks. *Journal of Competition Law and Economics*, 1:679–705.