Estimation of cost synergies from mergers without cost data: Application to U.S. radio *

Przemysław Jeziorski †

July 3, 2010

Abstract

This paper develops a new way to estimate cost synergies from mergers without using actual data on cost. The estimator uses a structural model in which companies play a dynamic game with endogenous mergers and product repositioning decisions. Such a formulation has several benefits over the widespread static merger analysis. In particular, it corrects for sample selection of more profitable mergers and captures follow-up mergers and post-merger product repositioning.

The framework is applied to estimate cost efficiencies after the deregulation of U.S. radio in 1996. The procedure uses the data on radio station characteristics and numerous acquisitions, without explicit need for cost data. It turns out that between 1996 and 2006 additional ownership concentration generated $2.5b per-year cost savings, which is about 10% of total industry revenue.

*I would like to thank: Lanier Benkard and Peter Reiss, Ilya Segal, Alan Sorensen, Benjamin Van Roy and Ali Yurukoglu, and participants of numerous seminars.

†Department of Economics, Johns Hopkins University

1 Introduction

The extent to which a potential merger generates cost efficiencies is often mentioned by managers as a major motivation to merge. Moreover, potential fixed cost savings generated by a merger are recognized by the Horizontal Merger Guidelines as a factor that can provide consumers with direct price-related as well as non-price-related benefits. Thus, for antitrust purposes one should evaluate cost savings in addition to measuring the decrease in competition. However, this approach is rarely used in practice, because in most cases reliable cost data are unavailable. This paper provides a solution to this problem, by proposing a method to estimate cost synergies without using any data on cost. This method requires only panel data on the ownership structure, product characteristics, and prices and quantities, information that in most cases is easily accessible.

Evaluating the underlying causes of ownership consolidation requires a dynamic model in which mergers are endogenous. However, most past empirical work analyzed mergers in a static framework and treats market structure as given. Papers by Nevo (2000), Pinkse and Slade (2004), Ivaldi and Verboven (2005) exogenously impose changes in market structure on a static equilibrium model and calculate counterfactual changes in prices and welfare. These models are very useful in addressing the short run impacts of mergers but do not account for changes in market structure that might happen as a result of a merger. Benkard, Bodoh-Creed, and Lazarev (2008) evaluate the longer run effects of a merger on market structure, but still treat it as an exogenous one-time event. Neither of these approaches allows for estimating the supply side determinants of mergers, such as cost synergies. Furthermore, the assumption that mergers are exogenous may create a selection bias that results in overestimating the cost synergies (we might pick up other unobserved components correlated with the propensity to merge). Furthermore, recent models assume away follow-up mergers and post-merger repositioning of products.

To address these issues, I propose a dynamic model in the spirit of Gowrisankaran (1999) in which mergers and product positioning are endogenous and are assumed to happen sequentially. Such an approach enables me to estimate the cost efficiencies of consolidation without any data on cost. It also eliminates the shortcomings mentioned earlier, because it incorporates the dynamic processes directly into the model. Moreover, endogenizing mergers allows for correction of sample selection by using a procedure in the spirit of Heckman (1979), adjusted for a dynamic game environment.

The model is subsequently applied to analyze ownership consolidation in the U.S. radio industry. The Telecommunications Act of 1996 increased local-market radio station ownership caps, triggering an unprecedented merger wave that had the effect of eliminating many small and independent radio owners. From 1996 to 2006, the average Herfindahl-Hirschman Index (HHI) in local radio markets grew from 0.18 to 0.26, the average number of owners in the market dropped from 16.6 to 12.4, and the average number of stations owned grew from 1.6 to 2.3. Such dramatic changes to the market structure have raised concerns about anti-competitive aspects of the deregulation (Leeper (1999), Drushel (1998), Klein (1997)). After estimating the model using the method of Bajari, Benkard, and Levin (2004), I find that the main incentives to merge in radio come from the cost side. Total cost side savings amount to \$2.5b per year, constituting about 10% of total industry revenue. Such cost synergies are an order of magnitude higher than the anti-competetive effects of these mergers identified by Jeziorski (2010). Moreover, the fact that consolidation leads to substantial cost side synergies leads me to conclude that the Telecom Act made radio advertising more competitive against other media, such as TV or the Internet.

To my knowledge, Gowrisankaran (1999) is the only applied paper that uses a dynamic framework to endogenize mergers. His analysis argued that merger dynamics are very important. The main drawback of his analysis is that it was never fit to real data. This was due in part to the complexity of his model and in part to the lack of a good dataset. To solve the complexity problem, I utilize the latest developments in the dynamic-games literature. These developments enable us to estimate very complicated models without explicitly solving them (Bajari, Benkard, and Levin (2004)). This paper also contributes to empirical literature on demand and cost curve estimation (this started with Rosse (1970) and Rosse (1967)), by accounting explicitly for the demand side incentives to merge. On the technical side, my model shares some similarities with Sweeting (2007). I concentrate on questions about incentives to merge and the impact of consolidation on welfare, while Sweeting focuses mainly on estimates of the format switching cost. My analysis also extends his model by adding a model of ad quantity choices and endogenous mergers. Another paper on a similar topic is O'Gorman and Smith (2008). They use a static oligopoly model to estimate the cost curve in radio. They find that the fixed cost savings when owning two stations is bounded between between 20% and 50% of per-station costs (I estimate this number to be 20%).

I supplement their estimates by accounting for selection bias, follow-up mergers and post-merger repositioning as outlined above.

This paper is organized as follows. Section 2 contains a flexible, structural merger model that can applied to many industries. The estimation procedure is discussed in Section 3. Section 4 describes the application of the framework to analyze the merger wave in the U.S. radio industry. Section 5 concludes the paper.

2 Merger and repositioning framework

This section presents the dynamic oligopoly model of an industry with differentiated products in the spirit of Ericson and Pakes (1995). The industry is modeled as a dynamic game and the players are companies holding portfolios of different products (brands). The modeling effort emphasizes the actions of companies changing the profolio of owned products, specifically rebranding and acquisitions. The model is general enough to encompass a number of different industries and types of competition, by allowing for a large range of different single-period profit functions and cost structures.

2.1 Industry basics

The industry is composed of M different markets that operate in discrete time over an infinite horizon. The payoff relevant market characteristics at time t are fully characterized by a set of covariates $d^{mt} \in \mathcal{D}$ that include demand shifters. In each market m, there are up to K_m operating firms and up to J_m active products. Let $o_j \in K_m$ be the owner of the product j. I assume that each product $j \in J_m$ is characterized by a triple $s_j^t = (f_j^t, \xi_j^t, o_j^t)$. In particular, $f_j^t \in F$ is a discrete characteristic, and $\xi_j^t \in \Xi$ is a continuous characteristic of the product. The state of the industry at the beginning of each period is therefore a duple $(s^t, d^t) \in \mathcal{S} \times \mathcal{D}$.

To simplify the further exposition define O_k^t to be the number of products owned by the firm k, and O_{-k}^t to be the number of products owned by its competitors.

2.2 Players' actions

Firms can undertake two types of actions: product acquisitions and product repositioning. I assume that acquisitions take place first and the results are common knowledge before the firms commence with repositioning.

In general, the product acquisition process can be very complicated. Firms can acquire any subset of products owned by competitors, and multiple firms can bid to acquire the same product. Therefore, the most general model of this process is likely to be intractable both analytically and numerically. Additionally, the model of mergers without additional structure is likely to generate multiple equilibria, which will significantly complicate its estimation. To solve these problems, I follow Gowrisankaran (1999) and I assume that the station acquisition process is sequential. Owners move in a sequence specified by a function $A : s^t \mapsto i$, where i is a permutation of the active owners' index $\{1, \ldots, K\}$. In addition, for notational purposes, I set $i(K+1) = K+1$.

Let $\omega^t_{i(k)}$ be the state of the industry observed by the k-th mover in the merger process, before making acquisition decisions. $\omega^t_{i(1)}$ is set to be equal to s^t. Additionally, every player observes a set of acquisition prices for all stations owned by competitors

$$P^t_k = \{\phi^t_{kj} : o^t_j \neq k\}$$

These prices are the outcomes of a bargaining process that is only a function of the current observable state $\omega^t_{i(k)}$. This assumption holds if $\omega^t_{i(k)}$ is the only payoff relevant variable for both the acquirer and the acquiree and the prices are determined by a Nash Bargaining Solution.

In addition to prices, the potential buyer observes a set of additive payoff/cost shocks from acquiring any competitor owned product $\phi^t_k = \{\phi^t_{kj} : o^t_j \neq k\}$ that is his private information. A player's $i(k)$ action involves specifying which subset of stations are to be acquired. I restrict attention to Markov strategies, so the acquisition policy is a mapping

$$a_k : (\omega^t_{i(k)}, \phi^t_k, P^t_k, d^t) \mapsto \{0,1\}^{O^t_{-k}}$$

After the decisions are made, a new ownership $\omega^t_{i(k+1)}$ is determined, and it becomes common knowledge. Player $a(k+1)$ proceeds with acquisitions, or if there are no move active players, the game moves to product repositioning.

A product repositioning involves decisions about changing discrete characteristics f_j^t of owned products, in exchange for paying a switching cost $C(f_j, f_j^{t+1})$. It is, similarly to acquisitions, a sequential process, and it is assumed that firms proceed according to the same sequence $i(k)$[1].

The first mover $i(1)$ in the repositioning process conditions his decision on the state of the industry after the acquisitions, i.e., the observable state $\tilde{\omega}_{i(1)}^t$ is equal to $\omega_{i(K+1)}^t$. In the same way the k-th mover $i(k)$ observers the repositionings done by all the previous movers. This information is summarized in $\tilde{\omega}_{i(k)}^t$. In addition to observing the state $\tilde{\omega}_{i(k)}^t$, the k-th mover observes payoff/cost shocks for all the products of any potential type $\psi_k^t = \{\psi_{kjf}^t : o_j^t = k, 1 \geq f \geq F\}$. The product repositioning policy is a Markov strategy given by the mapping

$$b_k : (\tilde{\omega}_{i(k)}^t, \psi_k^t, d^t) \mapsto F^{O_k^t}$$

When the choices of player $i(k)$ are made a new industry state $\tilde{\omega}_{i(k+1)}^t$ becomes a common knowledge.

After repositioning the new industry state (s^{t+1}, d^{t+1}) is determined. s^{t+1} is constructed by combining $\tilde{\omega}_{i(K+1)}^t$ with the values of a new continuous product characteristic ξ^{t+1} The following assumptions restrict the dynamics of ξ.

Assumption 2.1. *ξ_{jt} evolves as an exogenous Markov process, for example*

$$\xi_{jt} = \rho\xi_{jt-1} + \zeta_t \tag{2.1}$$

where ζ_t is a mean zero IID random variable.

Moreover, market covariates are also assumed to be exogenous and Markov

Assumption 2.2. *d^t evolves as an exogenous Markov process.*

These assumptions are made for simplicity of estimation. They could be potentially relaxed if more data is available. For example, if ξ is a product quality, one could assume that it is also a dynamic choice variable and estimate it directly from the observed investment.

When the new industry state is (s^{t+1}, d^{t+1}) realized firms then play a static competition game that yelds profits given by $\bar{\pi}_k(s^{t+1}, d^t)$.

[1]This assumption is made for the simplicity of exposition and might be easily relaxed.

2.3 Payoffs and equilibrium

Given the realizations of $(s^t, s^{t+1}, P^t, \psi^t, \phi^t, d^t)$ the per-period payoff for player k is given by the equation

$$\begin{aligned}\pi_k(s^t, s^{t+1}, &P^t, \psi^t, \phi^t, d^t) = \bar{\pi}_k(s^{t+1}, d^t) - F(s_k^t) + \sum_{j:o_j^t \neq k, o_j^{t+1}=k} (\phi_{kj}^t - P_{kj}^t) + \\ &+ \sum_{j:o_j^t=k, o_j^{t+1}\neq k} P_{o_j^{t+1}j}^t + \sum_{j:o_j^{t+1}=k} \left[\psi_{kjf_j^{t+1}}^t - I(f_j^{t+1} \neq f_j^t) C(f_f^t, f_j^{t+1})\right]\end{aligned} \tag{2.2}$$

where $F(s_k^t)$ is the fixed cost of owning portfolio s_k^t, and $\bar{\pi}_k$ is a one-shot profit from the portfolio.

Let $\mathbf{g} = (a_1, \ldots, a_K, b_1, \ldots, b_K)$ be a Markov strategy profile. It can be shown that this profile and an initial condition (s, d) determine the unique, controlled Markov process over states, acquisition prices P, payoff shocks ψ and ϕ, and market covariates d

$$\mathcal{P}(\mathbf{g}, s, d) \in \Delta(\mathcal{S} \times P \times \Psi \times \Phi \times \mathcal{D} \times \mathcal{T})$$

where $\mathcal{T}$ is a time horizon, and Δ is a set of probability measures. $\mathcal{P}$ is therefore a discrete time stochastic process on $\mathcal{S} \times P \times \Psi \times \Phi \times \mathcal{D}$. This process is also supplied with a filtration, such that the strategy profile $\mathbf{g}$ is measurable.

Each owner is maximizing the expected discounted sum of profits taking the strategies of opponents $\mathbf{g}_{-k}$ as given. The value function for player k is defined as

$$V_k(s, d|\mathbf{g}_k, \mathbf{g}_{-k}) = E_{\mathcal{P}(\mathbf{g},s,d)} \sum_{t=0}^{\infty} \beta^t \pi_k(s^t, s^{t+1}, P^t, \psi^t, \phi^t, d^t) \tag{2.3}$$

It is assumed that the markets are in a Markov Perfect Equilibrium, i.e., firms choose strategy profile $\mathbf{g}^*$, such that for all k

$$V_k(s, d|\mathbf{g}_k^*, \mathbf{g}_{-k}^*) \geq V_k(s, d|\mathbf{g}_k, \mathbf{g}_{-k}^*) \quad \forall \mathbf{g}_k. \tag{2.4}$$

For simplicity, I restrict my attention to symmetric equilibria. The next section describes the estimation procedure.

3 Estimation

Consider parameterizations of the fixed cost $F(s_k^t|\theta_F)$ and the switching cost $C(f_j^t, f_j^{t+1}|\theta_C)$. This section outlines a procedure, based on Bajari, Benkard, and Levin (2004), to obtain consistent estimators of θ_F and θ_C without using direct data on cost.

The procedure has two stages. The fist stage infers equilibrium behavior from the data on one or a set of similar industries. The second stage estimates the cost parameters for a particular industry by imposing the dynamic game equilibrium inequalities 2.4. The following subsection describes the data needed for this procedure to work.

3.1 Data

Consider an industry, or a set of similar industries, operating in M markets over the discrete time span T. Data is given by the set $X = \{x^{tm} : 1 \leq m \leq M, 1 \leq t \leq T\}$. Each point in the data x^{tm} describes the state of the industry at the beginning of the period $s^{tm} = (f^{tm}, \xi^{tm}, o^{tm})$, market covariates/demand shifters d^{tm}, and a set of transaction prices P^{mt}. The data does not have to contain any direct information on the cost. This is convenient since most of the data on cost suffers from accounting issues. Therefore direct cost estimates from the data might be unreliable.

To facilitate the inference process a standard assumption about the data generating process is made: that it is generated by a single MPE strategy profile $\mathbf{g}^*$. Crucially, the dataset needs to contain a reasonable amount of within market acquisitions and repositioning to allows it to identify equilibrium strategies. Sometimes it is possible to obtain such datasets within one industry (see U.S. radio in the application), however for most industries such datasets are unavailable. In this case, it is possible to pool similar industries to construct one dataset. To make this work one needs a slightly stronger assumption that equilibrium behavior is the same across the pooled industries.

The transaction prices are helpful but not necessary to identify the cost parameters. Estimation is possible without them but it requires more assumptions about the bargaining process during the acquisition, as well as much more computing power. The extra steps needed to proceed without the prices are mentioned in Appendix A.

In order to simplify the exposition all state variables are assumed to be observed. However, the procedure also applies to problems in which some payoff relevant information is unobserved to the econometrician. In many cases one can infer the unobserved state variable from a static estimation of the one-shot profit function $\bar{\pi}$. One example of such a case is Berry, Levinsohn, and Pakes (1995) estimator, which uses differences of static market shares to identify unobserved product quality. Moreover, there are numerous ways to proceed in case one cannot directly infer all the latent state variables. For example, one could supply the procedure from this chapter with an EM algorithm proposed by Arcidiacono and Miller (2010).

3.2 Policy estimation

For any strategy profile

$$\mathbf{g} = (a_1, \dots, a_K, b_1, \dots, b_K)$$

let $\text{Prob}_k^M(a_k|\omega_k, d_k)$, and $\text{Prob}_k^R(b_k|\tilde{\omega}_k, d_k)$, be the probabilities of taking acquisition and repositioning actions. The former is a probability measure on $\{0,1\}^{O_{-k}}$, and the latter on $\{1, \dots, F\}^{O_k}$. They are constructed by integrating out unobservable payoff shocks ϕ and ψ. The goal of this subsection is to provide a procedure that allows us to obtain the estimates of these probability measures. This procedure leverages on the sequentiality assumptions made in the previous section.

The first step of the procedure is constructing an auxiliary dataset using a sequential structure of the acquisition and repositioning process. For each t, the predefined sequence of player moves $i = I(s_t)$ specifies a mapping

$$(s_t, s_{t+1}) \mapsto (\omega_{i(1)}, \dots, \omega_{i(K)}, \tilde{\omega}_{i(1)}, \dots \tilde{\omega}_{i(K)})$$

This mapping is used to construct 3 sets. The first set describes the acquisition dynamics

$$Y_1 = \{(\omega_k^{tm}, d^{tm}, a_k^{tm}) : 1 \le k \le K, 1 \le m \le M, 1 \le t \le T\}$$

where a_k^{tm} is a vector of zeros and ones that indicates acquisition decisions for player k. The second set describes acquisition prices

$$Y_2 = \{(\omega_k^{tm}, d^{tm}, P_k^{tm}) : 1 \le k \le K, 1 \le m \le M, 1 \le t \le T\}$$

where P_k^{tm} is a vector of prices for all acquisitions of player k. The last set describes the repositioning

$$Y_3 = \{(\tilde{\omega}_k^{tm}, d^{tm}, F_k^{mt}) : 1 \le k \le K, 1 \le m \le M, 1 \le t \le T\}$$

where F_k^{mt} is a vector of chosen characteristics for products owned by firm k.

Set Y_1 is used to estimate the acquisition probability distribution Prob_k^M as a function of (ω, d). In a perfect world, one would like to employ a form of non-parametric multi-dimensional discrete choice estimator. However, in practice, the researcher is likely to face two problems: the large dimensionality of covariates (ω, d) and the large dimensionality of the Prob_k^M support (due to a big number of active products/companies that can be acquired).

The solution to the first problem is to employ a flexible parametric form

$$\widehat{\text{Prob}}_k^M(a_k|\omega_k, d_k, \theta_M)$$

that exhausts most of the information in the data. The asymptotics of such an estimator are similar to the non-parametric estimators in which the dimensionality of pseudo-parameters θ_M grow as the dataset becomes large.

The second problem is more severe and in most cases cannot be solved without additional assumptions. The following examples suggest different possible approaches.

Example 3.1 (One acquisition per period)**.** *If the acquisitions in the data tend to be rare, one could potentially assume that only one acquisition per owner is allowed each period. This reduces the decision space to only one dimension and enables direct application of any discrete choice model (for example logit or probit) on the data set* Y_1*.*

The second example suggests how to deal with multiple acquisitions

Example 3.2 (Independent acqusitions)**.** *In the case where the acquisition decisions are uncorrelated conditional on* ω_k *and* d_k *one could employ a discrete choice regression directly on* Y_1*, fixing* ω_k^{tm} *for all decisions in* $\tilde{a}_k^{tm}$*.*

The next solution makes more assumptions about the structure of the acquisition decision making within the firm.

Example 3.3 (Sequential acqusitions)**.** *Suppose that the acquisition decisions are made in a sequence, i.e., after observing* ψ_j *for a particular product, the firm decides about its acquisition without looking at the payoff shocks* ψ *for other stations. In this case one could further expand dataset* Y_1 *to incorporate the sequence of decisions within the firm. Because of the additive structure of payoffs and the fact that* ψ_j *are IID, one could consistently estimate* Prob_k^M *by using a discrete choice estimator on the extended dataset.*

If one were to observe the acquisition prices one could estimate the pricing function $P(\omega_k^{st})$

directly from the dataset Y_2. This could be achieved by employing the flexible parametric interpolation[2].

When estimating the repositioning probabilities Prob_k^R one faces similar problems, but additionally one has to deal with multinomial vs. binomial choice. The three examples of solutions to that problem presented previously also apply here.

Additionally, one could endogenize the continuous characteristic ξ and estimate it as a function of the state space using the methods presented in Bajari, Benkard, and Levin (2004). Depending on the interpretation of ξ, this might involve an additional model. In this paper however, ξ^t as well as d^t are treated as exogenous and Markov. The transition in this case can be estimated as a flexible parametric auto-regressive process.

In the next subsection I describe a second stage of the cost function estimator that uses the estimators of equilibrium policy and the transition of ξ and d^t obtained in the first step above.

3.3 Minimum distance estimator

For the second stage the parameters of the fixed cost θ_F and repositioning cost θ_R are estimated using a minimum distance estimator. The estimator is constructed using the MPE inequalities (2.4). The remainder of this section describes how I obtain estimates of the value functions in those inequalities.

The value function V_k (defined on the equation (2.3)) can be separated into four parts.

$$V_k^t = A_k^t + \theta_\phi B_k^t + \theta_\psi C_k^t + D_k^t$$

where

$$A_k^t = E\sum_{r=t}^{\infty} \beta^{r-t}\bar{\pi}_k(s^t, d^t) + \sum_{j:o_j^r=k,o_j^{r+1}\neq k} P^r_{o_j^{r+1}j} - \sum_{j:o_j^r\neq k,o_j^{r+1}=k} P^r_{kj}$$

is the expected stream of advertising revenues,

$$B_k^t = E\sum_{r=t}^{\infty} \beta^{r-t} \sum_{j:o_j^r\neq k,o_j^{r+1}=k} \phi^r_{kj}$$

[2]Sometimes the dataset on prices is sparse, i.e., one does not observe prices for every deal. In this case more simplifying assumptions about the pricing process are needed.

is the expected stream of acquisition payoff/cost shocks,

$$C_k^t = E\sum_{r=t}^{\infty}\beta^{r-t}\sum_{j:o_j^{r+1}=k}\psi^t_{kjf_j^{r+1}}$$

is the expected stream of repositioning payoff/cost shocks, and

$$D_k^t = E\sum_{r=t}^{\infty}\beta^{r-t}\left[F(s_k^r|\theta_F)+\sum_{j:o_j^{r+1}=k}\mathbf{1}(f_j^{r+1}\neq f_j^r)C(f_j^r,f_j^{r+1}|\theta_C)\right]$$

is the expected stream of fixed costs and repositioning costs. The extra parameters θ_ϕ and θ_ψ are needed because the first stage estimation requires normalization of the variances of ϕ and ψ.

Accounting for B_k^t in the simulation of profits from a merger takes care of selection on unobservables, as apposed to the usual static approach to mergers. Given the merger decision a_{jk}^{tm}, the contribution of unobserved profits is $\theta_\phi E[\phi_{jk}^{tm}|a_{jk}^{tm}]$. Because a company observes the payoff shock before making an acquisition, the mergers that occur are selected for high value of ϕ_{jk}^{tm} When ϕ has zero mean, it is the case that $E[\phi_{jk}^{tm}|a_{jk}^{tm}=1]>0$. Failing to account for that (i.e. assuming that $E[\phi_{jk}^{tm}|a_{jk}^{tm}=1]=E[\phi_{jk}^{tm}]=0$) would cause underestimation of profits from mergers and overestimation of fixed cost synergies [3]. The same point can be made about the selection on unobservables when repositioning products and inclusion of C_k^t.

Note that only the last part of D_k^t depends on the parameters of interest θ_F and θ_C and the value function is linear θ_ϕ and θ_ψ. Therefore, to compute the value function for different parameter values one does not need to re-simulate the industry path (s^t,d^t); moreover, one does not need to recompute any of A_k^t, B_k^t, C_k^t [4]. This saves a large amount of processing power and makes the estimator feasible using today's computers.

Following the inequality (2.4), let V_k^t be an equilibrium value function for player k, $V_k(\cdot|\mathbf{g}_k^*,\mathbf{g}_{-k}^*)$. Additionally, define a suboptimal value function $\tilde{V}_k^t$ to be $V_k(\cdot|\mathbf{g}_k,\mathbf{g}_k^*)$ for some off-equilibrium strategy $\mathbf{g}_k$. In equilibrium, I know that $\max\{\tilde{V}_t^k - V_k^t, 0\}=0$ for the true values of θ_M and θ_R.

[3] When using any of the dynamic likelihood estimators proposed in the previous subsection and assuming that ϕ is a difference of two independent Type I extreme value random variables, $E[\phi|a=1]$ can be reduced to $-\log(p)-\frac{1-p}{p}\log(1-p)$, where p is a probability of acquisition.

[4] In most cases A_k^t is the hardest to compute because computing $\bar{\pi}$ may involve solving a one-shot Nash equilibrium price or a quantity setting game.

Thus, I define a minimum distance estimator

$$(\hat{\theta}_M, \hat{\theta}_R) = \text{argmin} \frac{1}{K \times T \times M} \sum_{k,t,m} \frac{1}{A_k^{tm}} \left\| \max\{\tilde{V}_k^{tm} - V_k^{tm}, 0\} \right\|$$

According to the results in Bajari, Benkard, and Levin (2004) this estimator is consistent and asymptotically normal. This finishes the description of the estimator. An example of its application is contained in the next section.

4 Application

In this section, I describe how to use above framework to estimate merger synergies from ownership consolidation in the U.S. radio industry. In the next subsection I give a brief review of the industry. The second subsection presents the tailored version of the estimation algorithm. The last subsection presents and discusses the results.

4.1 Industry and data description

Radio is an important medium in the U.S., reaching about 94% of Americans twelve years old or older each week. Moreover, the average consumer listens to about 20 hours of radio per week and between 6am and 6pm more people use radio than TV or print media[5]. There are about 13,000 commercial radio stations that broadcast in about 350 local markets nationwide. Before 1996, this industry had ownership limitations both nationally and locally, preventing big corporations from entering the market and thereby sustaining a large degree of family based ownership. This situation changed with the Telecom Act of 1996 which, among other things, raised the ownership caps in the local markets (see Table 1).

This triggered an unprecedented merger and product repositioning wave that completely reshaped the industry. Figure 1 contains the average percentage of stations that switched owners and that switched formats. Between 1996 and 2000 more than 10% of stations switched owners annually. After 2000 the number dropped to less than 4%. Greater ownership concentration in the 1996-2000 period was also associated with more format switching. The percentage of stations

[5]Source: A.Richter (2006)

# of active stations	Old ownership cap	New cap
45+	4	8
30-44	4	7
15-29	4	6
0-14	3	5

Table 1: Change in the local ownership caps introduced by the 1996 Telecom Act.

that switched formats peaked in 1998 and 2001 at 13%. In effect, the Herfindahl-Hirschman Index (HHI) in the listenership market grew from 0.18 in 1996 to about 0.3 in 2006.

The impact of this consolidation on consumer surplus has been studied before using a static demand and supply approach. For example Jeziorski (2010) (Chapter 2 of this thesis), finds that consolidation of ownership in this industry was harmful to advertisers, causing \$300m loss in advertiser surplus, but beneficial to listeners, raising the welfare by 1%.

In order to analyze the supply side effects of this consolidation, I compiled a dataset [6]. on stations in the 88 markets studied by Jeziorski (2010). The data contains ownership for each station o_j, and station format f_j. It uses the estimates of station quality ξ_j, contained in Jeziorski (2010). I also observe each acquisition made in this market and the average acquisition price.

4.2 Static profits

The static profit function is taken directly from Jeziorski (2010). Radio station owners draw their revenue from selling advertising and each advertising slot is priced on a per listener basis. The total profit of the owner k is equal to

$$\bar{\pi}_k(s,d) = \sum_{j:o_j=k} r_j(q^*,s,d)p_j(q^*,s,d)q_j^*$$

where q^* are the equilibrium advertising quantities chosen in the static oligopoly game, r_j is the number of listeners and p_j is the price per listener. In this paper, I treat the estimates of this profit function as given; however, I do correct the standard errors of the dynamic estimates by

[6]Data is constructed using the software provided by *BIA Financial Network Inc.* and Media Market Guides by SQAD

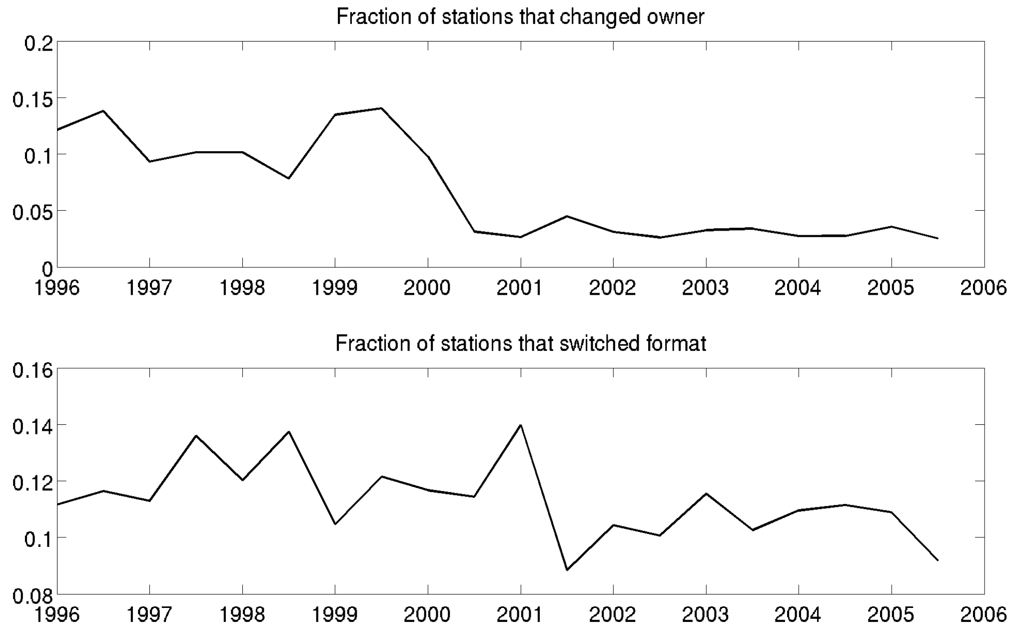

Figure 1: Dynamics of station acquisition and format switching

accounting for the noise introduced by estimating profit function.

The only difference between the baseline model in Jeziorski (2010) and the profit function used in this chapter is that the marginal cost of production is set to zero and format substitution matrix Ω is assumed to be diagonal. I made these assumptions for computational reasons.

4.3 Estimation details

The estimation is a direct application of the framework desribed in subsection 3. The model endogenizes acquisition decisions and format switching decisions. The dynamics in an unobserved radio station quality ξ is assumed to be exogenous.

The first piece of the model that needs to be specified is the function $I(s^t, d^t)$, that prescribes the sequence of moves firms make in the merger and repositioning process. Following Gowrisankaran (1999), I assume that firms with the biggest total market shares move first. This is motivated by the fact that the bigger players in the market might a have first-mover advantage over smaller players. The acquisition price is assumed to be constant within market and equal to the observed mean acquisition price.

To estimate the merger probability I use the method outlined in the Example 3.3. Each owner considers, one at a time, stations to acquire, starting from the one with the highest quality measure ξ_j, and moving down according to ξ_j [7]. A flow chart of the merger process is presented in the Appendix B. Such structure enables expanding the data structure on acquisitions within the firm

$$(\omega_k^t, a_k^t) \mapsto (\omega_{jk}^t, a_{jk}^t)_{j=1}^{O_{-k}^t}$$

where O_{-k}^t is the number of stations owned by competitors. If we assume that ψ is a difference of two extreme value distributions and is also revealed in a sequence, one can consistently estimate a probability of merger Prob_k^M, by running a regular logit regression on this extended dataset.

The covariates in the logit regression should reflect the information about the state space contained in the data. In a perfect world one would use a very flexible index function of the state space variables. However, because of high dimensionality of the state space, such an approach requires too many degrees of freedom, and quickly exhausts all the information available in the data. To overcome this problem, I use a linear index function of several statistics about the state space computed from the data [8]. The full set of covariates can be found in Table 5 in Appendix C.

A similar strategy can be employed to estimate the format switching process. The flow chart describing this process is contained in Appendix B. Assuming that firms switch formats sequentially dictates the following dataset expansion

$$(\omega_k^t, a_k^t) \mapsto (\omega_{jk}^t, a_{jk}^t)_{j=1}^{O_{-k}^t}$$

Using this auxiliary dataset one can apply a multinomial logit model to estimate the format switching probabilities Prob_k^R. The restriction on the index function also applies in this case, so I use only a limited set of covariates (given in Table 6 in Appendix C).

In the second stage of the estimation, I parametrize the fixed cost function

$$F(s_k^{tm}) = \theta_{C1} \times \text{POP}_m \times n_k^{tm}\theta_{C2} \tag{4.1}$$

where POP_m is a population of the market m and n_{kt} is the number of stations owned by player k at time t. Parameter θ_{C2} dictates the amount of cost synergies from owning multiple stations.

[7] Choice of ξ_j as an ordering characteristic is motivated by the fact that it is a vertical measure of profitability.

[8] a similar approach can be found in Sweeting (2007), Ryan (2005), Ryan and Tucker (2006), and Ellickson and Arie (2005).

I also assume a constant format switching cost that is proportional to the population. Those assumptions are motivated by the fact that Jeziorski (2010) finds that most of the variation in marginal cost of radio operations between can be explained by the variation in total population.

In the second stage, I simulate the value function only for the owner with the biggest market share at each data point (s^{tm}, d^{tm}). These simulations are done according to the Algorithms 2 and 3. The suboptimal value function $\tilde{V}_k$ is obtained by multiplying the merger and format switching probability by a uniform $[.95, 1.05]$ random variable. When choosing the size of the perturbations one faces a bias and variance trade-off. When the size is too small the estimator start picking up the noise from the simulations instead of the sub-optimality of the strategy, decreasing the efficiency of the estimator. When the size is chosen to be too big, the bounds of the estimator become very large creating potential bias. The chosen perturbation is a compromise between those two factors.

4.4 Results

This subsection describes the results of the estimation. The exposition is divided into two parts. First, I present the policy function estimates. Then, I report the main results on fixed cost and switching cost synergies.

4.4.1 First stage: Policy function

Tables 7 and 8 report coefficients from a purchase strategy probit approximation. They reveal that owners with larger market shares are more likely to purchase new stations and are less likely to sell. Also, there are synergies when purchasing multiple stations. The coefficient on the first purchase dummy `PUR0` is negative while coefficients on dummies for multiple purchases are positive. This indicates that it is easier to negotiate the purchase of many stations, or even an entire company at once, than a single station. The number of owned stations in the format (the `FORMAT` variable in the table) has a negative influence on purchase decisions. This is evidence for diversification. The coefficient of station quality is positive which suggests that stations with higher quality are purchased more often.

Table 9 presents the influence on future format of the following covariates: change of ownership dummy, AM/FM status, and previous format. The negative coefficient of a Spanish format in the first row of the table suggests that when a station is purchased it is less likely to switch to Spanish format. On the other hard, the positive coefficient of AC tells us that change in ownership is correlated with switching to the Adult Contemporary format. The second column of the table shows that `FM` stations are likely be of Rock or CHR format, and not so likely to be of News/Talk format. The remaining rows of the table describe the Markov dynamics of formats. The diagonal cells have much higher numbers than the off-diagonal ones, which reflects the fact that staying in the current format is much more probable than switching.

Table 10 presents the relationship between the current demographic composition of the market format switching decisions. In addition, Table 11 contains similar information concerning the dynamics of the demographics (the difference between two consecutive periods) and format switching. One can observe many patterns that suggest firms respond to the current state of population demographics as well as to the dynamics of population demographics. For example, a larger current population and growth of the Hispanic population is ralated to the stations switching to a Hispanic format. One can observe a similar pattern for Blacks and the Urban format, as well as for older people and the News/Talk format. Those patters largely reflect correlations between tastes for formats and demographics described in Jeziorski (2010).

4.4.2 Second stage: Fixed and switching cost

The estimated parameters of the fixed cost equation (4.1) are as follows: $\hat{\theta}_{C1} = 0.69$ and $\hat{\theta}_{C2} = 0.59$. Table 2 interprets the economic significance of these parameters in terms the amount of saved fixed costs per year if two stations are commonly owned compared to being separate companies. Since the amount of cost synergies depends on the market population, only three representative markets are presented. Los Angeles is the biggest market in the sample and the cost savings in that market amount to about \$4.4m per-year (roughly 10% of the revenue of a big station). Knoxville is representative of medium markets and has about \$0.23m of such cost savings, and Bismark, a small market, has about \$34k of savings. Table 3 presents total cost savings from all mergers after the Telecom Act was passed. It turns out that the merger activity lowered the fixed cost of providing radio programming by almost \$2.5b, amounting to almost 10% of the total revenue of the industry. Compared to that, the impact on advertiser surplus identified in Jeziorski (2010) is very small. This leads me to conclude that the deregulation of 1996 provided substantial operational

Market	Los Angeles	Knoxville	Bismarck
Population	13m	.7m	100k
Savings per year	\$4.4m	\$.23m	\$34k

Table 2: Savings when two stations are owned by the same firm vs. operating separately

	Consumer Surplus	Advertiser Surplus	Fixed Cost
Impact of Telecom Act	+1%	-\$300m	-\$2.450m

Table 3: Total cost savings created by mergers after 1996, compared to demand effects from Jeziorski (2010)

efficients that outweigh negative impacts on advertiser welfare.

The last set of estimates concern the product repositioning costs. The estimate of the cost parameter $\hat{\theta}_C$ is 2.1. The repositioning cost for each market is the population of that market multiplied $\hat{\theta}_C$. Examples of this cost are given in Table 4. The table suggests this cost is about the yearly revenue of a big station. Such a huge repositioning cost can justify some of the behavior found when analyzing the merger probabilities; namely, stations tend to stay away from purchasing the formats they already have. If the format switching costs were low, the optimal thing to do would be to purchase stations close to your portfolio to get rid of competition and rebrand them to avoid cannibalization. However, if the switching costs are high, it might be optimal to avoid paying them and purchase a station further away. The previous subsection and Sweeting (2008) presest the evidence of the latter type of behavior, reinforcing the finding of high switching cost estimates.

Market	Los Angeles	Knoxville	Bismarck
Switching cost	\$27m	\$1.5m	\$0.2m

Table 4: Format switching cost for chosen markets

5 Conclusions

This paper proposed a new estimator of a production cost curve that enables the identification of cost synergies from mergers. The estimation uses inequalities representing an equilibrium of a dynamic game with endogenous mergers and product repositioning decisions.

The biggest advantage of this estimator is that it enables the identification of the cost curve just from merger decisions, without using cost data. Since reliable cost data is very hard to obtain, the cost side analysis of mergers was very hard to perform. This method is able to solve this problem, and provides a powerful tool for policy makers to improve their merger assessments.

Since the proposed method is based on a fully dynamic framework, it additionally solves many of the problems of static merger analysis. First of all, endogenizing the merger decision allows for sample selection on unobservables in the estimation and correcting for the fact that only the most profitable mergers are carried out. Moreover, I allow for follow-up mergers and merger waves. Additionally, endogenizing product characteristics enables correction for post-merger product repositioning.

The estimator belongs to a class of indirect estimators proposed by Hotz, Miller, Sanders, and Smith (1994) and Bajari, Benkard, and Levin (2004). Therefore, it shares all the benefits of those estimators, such as conceptual simplicity of implementation and computational feasibility, because it avoids the computation of an equilibrium. However, it also shares their downsides, such as a loss in efficiency.

The estimator was applied to analyze the cost side benefits of a deregulation of the U.S. radio industry. It turns out that the consolidation wave in that industry between 1996 and 2006 provided substantial cost synergies. These amounted to about 2 billion dollars per, year and constitute about 10% of industry revenue. Such benefits are an order of magnitude larger than potential losses in advertiser welfare found by Jeziorski (2010). This provides a significant argument for the supporters of a deregulation bill, and serves as an example of how cost curve estimation can provide additional insights supplementing traditional merger analysis.

References

Aguirregabiria, V., and P. Mira (2007): "Sequential Estimation of Dynamic Discrete Games," *Econometrica*, 75(1), 1–53.

Arcidiacono, P., and R. Miller (2010): "CCP Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity," Discussion paper, Duke University.

A.Richter, W. (2006): *Radio: Complete Guide to the Industry*. Peter Lang Publishing.

Ashley Herweg, G. H. (1997): *Radios Niche Marketing Revolution FutureSell*. Focal Press.

Bajari, P., C. L. Benkard, and J. Levin (2004): "Estimating Dynamic Models of Imperfect Competition," NBER Working Papers 10450, National Bureau of Economic Research, Inc.

Benkard, C. L., A. Bodoh-Creed, and J. Lazarev (2008): "Simulating the Dynamic Effects of Horizontal Mergers: U.S. Airlines," Discussion paper, Stanford University.

Bernile, G., E. Lyandres, and A. Zhdanov (2006): "A Theory of Strategic Mergers," Discussion paper, EFA Zurich Meetings Paper.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4), 841–90.

Berry, S. T., and J. Waldfogel (1999): "Mergers, Station Entry, and Programming Variety in Radio Broadcasting," Working Paper 7080, National Bureau of Economic Research.

CRA International (2007): "Expost Merger Review: An Evaluation of Three Competition Bureau Merger Assessments," Discussion paper, CRA International.

Department of Justice (1997): "Horizontal Merger Guidelines," Discussion paper, Department of Justice.

Doraszelski, U., and M. Satterthwaite (2004): "Foundations of Markov-Perfect Industry Dynamics: Existence, Purification, and Multiplicity," 2004 Meeting Papers 189, Society for Economic Dynamics.

Drushel, B. E. (1998): "The Telecommunications Act of 1996 and Radio Market Structure," *Journal of Media Economics*, 11.

Dube, J.-P. H., J. T. Fox, and C.-L. Su (2009): "Improving the Numerical Performance of BLP Static and Dynamic Discrete Choice Random Coefficients Demand Estimation," NBER Working Papers 14991, National Bureau of Economic Research, Inc.

Ellickson, P., and B. Arie (2005): "The Dynamics of Retail Oligopolies," Discussion paper.

Ericson, R., and A. Pakes (1995): "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62(1), 53–82.

Federal Communications Commision (2008): "FCC's Review of the Broadcast Ownership Rules," `http://www.fcc.gov/cgb/consumerfacts/reviewrules.html (accessed May 7, 2008)`.

Gal-Or, E., and A. Dukes (2006): "On the Profitability of Media Mergers," *Journal of Business*, 79(2), 489–526.

Gandhi, A. K., L. M. Froeb, S. T. Tschantz, and G. J. Werden (2005): "Post-Merger Product Repositioning," *SSRN eLibrary*.

Gowrisankaran, G. (1999): "A Dynamic Model of Endogenous Horizonal Mergers," *RAND Journal of Economics*, 30(1), 56–83.

Heckman, J. J. (1979): "Sample Selection Bias as a Specification Error," *Econometrica*, 47(1), 153–161.

Hotz, V. J., R. A. Miller, S. Sanders, and J. Smith (1994): "A Simulation Estimator for Dynamic Models of Discrete Choice," *The Review of Economic Studies*, 61(2), 265–289.

Ivaldi, M., and F. Verboven (2005): "Quantifying the effects from horizontal mergers in European competition policy," *International Journal of Industrial Organization*, 23(9-10), 669–691.

Jeziorski, P. (2010): "Impact of mergers and changes in product diversity on split of surplus in two-sided markets: Case of U.S. radio industry," Discussion paper, Stanford University, Working Paper.

Klein, J. I. (1997): "DOJ Analysis of Radio Mergers," *speech delivered in Washington DC*, http://www.usdoj.gov/atr/public/speeches/1055.pdf.

Leeper, S. E. (1999): "Game of Radiopoly: An Antitrust Perspective of Consolidation in the Radio Industry," *Fed. Comm. L.J.*, 52(473).

Nevo, A. (2000): "Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry," *RAND Journal of Economics*, 31(3), 395–421.

O'Gorman, C., and H. Smith (2008): "Efficiency Gain from Ownership Deregulation: Estimates for the Radio Industry," CEPR Discussion Papers 6699, C.E.P.R. Discussion Papers.

Pesendorfer, M. (2005): "Mergers Under Entry," *RAND Journal of Economics*, 36(3), 661–679.

Pinkse, J., and M. E. Slade (2004): "Mergers, brand competition, and the price of a pint," *European Economic Review*, 48(3), 617 – 643.

Rodrigues, V. (2001): "Endogenous mergers and market structure," *International Journal of Industrial Organization*, 19(8), 1245–1261.

Rosse, J. N. (1967): "Daily Newspapers, Monopolistic Competition, and Economies of Scale," *The American Economic Review*, 57(2), 522–533.

——— (1970): "Estimating Cost Function Parameters without Using Cost Data: Illustrated Methodology," *Econometrica*, 38(2), 256–75.

Ryan, S. (2005): "The Costs of Environmental Regulation in a Concentrated Industry," Working Papers 0510, Massachusetts Institute of Technology, Center for Energy and Environmental Policy Research.

Ryan, S., and C. Tucker (2006): "Heterogeneity and the Dynamics of Technology Adoption," Working Papers 06-26, NET Institute.

RYSMAN, M. (2004): "Competition between Networks: A Study of the Market for Yellow Pages," *The Review of Economic Studies*, 71(2), 483–512.

SALANT, S. W., S. SWITZER, AND R. J. REYNOLDS (1983): "Losses from Horizontal Merger: The Effects of an Exogenous Change in Industry Structure on Cournot-Nash Equilibrium," *The Quarterly Journal of Economics*, 98(2), 185–199.

STAHL, J. (2009): "A dynamic analysis of consolidation in the broadcast television industry," Working paper, Boston University.

SWEETING, A. (2007): "Dynamic Product Repositioning in Differentiated Product Markets: The Case of Format Switching in the Commercial Radio Industry," NBER Working Papers 13522, National Bureau of Economic Research, Inc.

——— (2008): "The Effects of Horizontal Mergers on Product Positioning: Evidence from the Music Radio Industry," working paper, Duke University.

YI, S.-S. (1997): "Stable Coalition Structures with Externalities,," *Games and Economic Behavior*, 20(2), 201 – 237.

Appendices

A Estimation without acquisition prices

In case the pricing function $\hat{P}^r_{jk}$ cannot be estimated in the first state because of data constraint, one could employ a bargaining model for infer it. Suppose one employs a parametrization $\hat{P}(\omega|\theta_P)$. For an initial value of parameters θ^0_P one could compute a surplus from acquisition of the product j by an owner k using simulated $\hat{V}^t_k$ and $\hat{V}^t_{k'}$ where k' is the current owner of product j. Then using a bargaining model one could infer prices and fit a new parametrization θ^1_P. If repeating this procedure leads to convergence, then obtain a parametrization $\hat{\theta}_P$ and value functions $\hat{V}^t_k$ that are consistent with eachother. The detailed description of this procedure is given in the Algorithm 1. The big dowside of this approch is that one needs resolve this procedure for any set of cost parameters and cannot take advantage of linearing of the value function. It makes the procedure infeasible to use for large datasets because of computational burden. However, given the rapid hardware development it is reasonable to think it it would be feasible in the near future.

Algorithm 1: Estimator without price data

Take any θ^0_P;

Let $r = 0$;

repeat

  Simulate the value functions $\hat{V}^r$ using pricing process $\hat{P}(\omega|\theta^r_P)$;

  Compute surplus from any acquisition using the simulated value functions;

  Compute acquisition prices $\hat{P}_{jm}$ by applying any bargaining game;

  Fit new parameters θ^{r+1}_P using $\hat{P}_{jm}$;

until *convergence of* θ^r_P ;

B Radio acquisition and format switching algorithms

This section of the appendix contains a detailed flows of the algorithms used to simulate the value function from section 4.

Algorithm 2: Merger algorithm

Let $\omega_1^r = s^r$;

foreach *firm k in a sequence $I(s^r)$* **do**

  Let J_{-k} be a set of stations not owned by k sorted by ξ_j^r;

  foreach *station j in J_{-k}* **do**

    Set purchase price $P_{jk}^r = \bar{P}^m$;

    Compute acquisition probability $\widehat{\text{Prob}}^M(\omega_k^r, d^t)$;

    Draw a random number u from $U[0,1]$;

    if $u \leq \widehat{\text{Prob}}^M$ **then**

      Increase $A_{\text{old owner}}^r$ by $\beta^{r-t} P_{jk}^r$;

      Decrease A_k^r by $\beta^{r-t} P_{jk}^r$;

      Update ω_k^r for acqusition;

      Increase B_k^r by $\beta^{r-t} E[\phi|\text{acquisition}]$;

    end

  end

  Let $\omega_{k+1}^r = \omega_k^r$;

end

Algorithm 3: Format switching algorithm

Let $\tilde{\omega}_1^r = \omega_{K+1}^r$;

foreach *firm k in a sequence $I(s^r)$* **do**

  Let J_k be a set of stations owned by k sorted by ξ_j^r;

  foreach *station j in J_k* **do**

    Compute repositioning probabilities $\widehat{\text{Prob}}_k^R(\tilde{\omega}_k^r, d^r)$;

    Simulate the future characteristic f_j^{r+1};

    Increase C_k^r by $\beta^{r-t} E[\psi|f_j^r]$;

    if *the f_j changed* **then**

      Update $\tilde{\omega}_k^r$;

      Remember the repositioning for a computation of D_k^r ;

    end

  end

  Let $\tilde{\omega}_{k+1}^{tm} = \tilde{\omega}_k^{tm}$;

end

C Policy function covariates

This section of the appendix contains tables of covariates used in the first stage in the estimation in section 4.

Format switching strategy

`PUR`	Dummy equal to 1 if station was recently purchased
`FM`	AM/FM dummy, equals to 1 if considered station is FM
`FORMAT`	Past format dummies
`PORT_F`	Number of stations owner in format `F`
`PORT_COMPJ_F`	Number of stations competitor `J` owns in format `F`, competitors of ranking 4 or higher are pooled
`XI_PORT_F`	Average quality of stations owner in format `F`
`XI_PORT_COMPJ_F`	Average quality of stations competitor `J` owns in format `F`, competitors of ranking 4 or higher are pooled
-	Demographic characteristics of the market

Table 5: Covariates for the format switching strategy multinomial logic regression.

Purchase strategy

OWNER1...OWNER4	Dummies that are equal to the ranking of the player in terms of total market share of owned stations. If ranking is lower that 4 we activate the fourth dummy
PAST_OWNER1...PAST_OWNER4	Ranking of the previous owner of the station amongst the competitors.
TRIAL	Describes how many stations did this player considered to purchase already this period. For explanation of sequential purchase decision process look in Section 4.3
PUR0...PUR3	Dummies describing number of stations already purchased
FORMAT	Number of stations owned in the format of considered station
FORMAT_COMP1...FORMAT_COMP4	Number of stations owned by competitors in the considered station, by ranking. FORMAT_COMP4 are pooled competitors with ranking of 4 or higher
FM	AM/FM dummy, equals to 1 if considered station is FM
PORT_F	Number of stations owner in format F
PORT_COMPJ_F	Number of stations competitor J owns in format F, competitors of ranking 4 or higher are pooled
XI	Average quality of stations owned in the format of considered station
XI_COMP1...XI_COMP4	Average quality of stations owned by competitors in the considered station, by ranking. XI_COMP4 are pooled competitors with ranking of 4 or higher
XI_PORT_F	Average quality of stations owner in format F
XI_PORT_COMPJ_F	Average quality of stations competitor J owns in format F, competitors of ranking 4 or higher are pooled
-	Dummies of the format of considered station interacted with demographic characteristics of the market

Table 6: Covariates for the purchase strategy logic regression.

D Frist stage estimates: Dynamic model

	Top 1 Owner	Top 2 Owner	Top 3 Owner
Buyer	0.5127	0.3423	0.2608
Seller	−0.3772	−0.2792	−0.0257

Table 7: Station purchase policy estimates - buyer/seller dummies

	Estimator
`PUR0`	−2.6082
`PUR1`	0.7548
`PUR2`	0.4279
`PUR3`	0.2463
`FORMAT`	−0.0534
`FORMAT_COMP1`	−0.0038
`FORMAT_COMP2`	−0.0556
`FORMAT_COMP3`	0.0728
`FORMAT_COMP4`	−0.0428
`FM`	0.0151
`STATION_XI`	−0.1069
`XI`	0.0596
`XI_COMP1`	0.0270
`XI_COMP2`	0.0712
`XI_COMP3`	0.0767
`XI_COMP4`	−0.0117

Table 8: Station purchase policy estimates - other variables

	AC	Rock	CHR	Urban Alt.	News Talk	Country	Spanish	Other
`PURCHASE`	0.30	−0.14	0.04	−0.07	0.05	0.03	−0.23	−0.22
`FM`	1.26	1.54	1.35	1.06	−0.25	1.31	0.56	0.85
AC	3.70	−0.47	−0.34	−0.86	−0.43	0.37	−0.66	−0.44
Rock	−0.27	4.41	−0.58	−0.18	−0.10	0.48	−0.32	−0.21
CHR	−0.24	−0.42	4.38	−0.06	−0.19	0.00	−0.14	−0.35
Urban Alt.	−0.49	0.05	−0.35	4.06	−0.17	0.48	−0.15	−0.22
News Talk	−1.00	−0.84	−0.82	−1.29	3.89	0.25	−0.80	−0.93
Country	−1.14	−1.01	−1.06	−1.35	−0.63	4.76	−0.73	−1.15
Spanish	−1.61	−1.45	−1.30	−1.61	−1.20	−0.29	3.10	−1.42
Other	−0.89	−1.07	−1.31	−1.27	−0.86	0.00	−1.22	3.02
Dark	−2.18	−2.42	−2.50	−2.62	−1.61	−0.72	−1.60	−1.31

Table 9: Format switching policy estimates - format dynamics

	AC	Rock	CHR	Urban Alt.	News Talk	Country	Spanish	Other
Age 12-17	0.00	−0.27	0.04	−0.50	−0.33	−0.67	−0.50	−0.32
Age 18-24	0.00	−0.31	−0.26	−0.69	0.31	0.00	−0.42	−0.36
Age 25-34	−0.54	0.00	0.02	−0.37	−0.14	−0.99	−0.06	−0.32
Age 35-44	−0.48	−0.00	−0.20	−0.32	−0.06	−1.17	−0.42	−0.08
Age 45-49	−0.46	0.00	−0.93	−0.61	0.23	−0.89	−0.81	−0.09
Age 50-54	−0.44	−0.41	−1.36	−0.67	0.42	−0.82	−0.62	−0.09
Age 55-64	0.00	−0.64	−1.49	−0.68	0.34	−0.77	−0.42	−0.16
Gender	−0.41	−0.23	−0.43	−0.54	−0.00	−0.84	−0.34	−0.21
Some HS	−0.38	−0.49	−0.41	−0.33	−0.27	−0.13	0.06	0.02
HS Grad.	0.19	0.00	−0.52	−0.32	−0.84	−0.29	−0.90	−0.19
Some College	−0.12	−0.34	−0.72	−0.70	0.23	−0.45	−0.45	−0.03
Income 0-25k	−0.16	−0.83	−0.32	−0.13	−0.35	−0.43	−0.52	−0.03
Income 25k-50k	−0.06	−0.54	0.14	−0.39	−0.33	−0.34	−0.13	0.00
Income 50k-75k	−0.07	−0.02	−0.54	−0.22	0.21	−0.39	−1.10	−0.17
Black	−0.99	−0.58	0.00	1.25	−0.44	−1.11	−0.54	−0.26
Hispanic	−0.55	0.19	−0.36	−0.06	−0.49	−0.20	2.42	−0.56

Table 10: Format switching policy estimates - current demographics

	AC	Rock	CHR	Urban Alt.	News Talk	Country	Spanish	Other
Age 12-17	0.00	0.00	0.00	6.69	−5.06	0.00	9.33	0.00
Age 18-24	−7.73	3.44	17.89	0.00	0.00	−12.76	0.00	6.06
Age 25-34	4.29	0.00	0.00	0.00	−1.35	5.23	4.32	−3.59
Age 35-44	2.65	0.00	5.23	1.83	−4.83	0.00	2.67	1.73
Age 45-49	−3.31	0.00	9.04	0.00	2.31	−3.45	−2.98	2.59
Age 50-54	−3.27	0.00	−2.60	−1.95	1.63	0.04	−3.37	0.00
Age 55-64	−4.57	−3.19	−7.50	0.00	7.73	0.00	−1.12	0.00
Gender	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Some HS	−0.03	−0.06	1.14	0.33	1.08	−0.06	−0.34	−1.09
HS Grad.	−0.56	0.00	1.18	0.90	0.84	−0.16	−0.31	−0.47
Some College	−0.40	−0.64	0.50	0.24	0.36	0.00	1.33	−0.89
Income 0-25k	0.43	0.37	0.05	0.20	0.32	0.33	−0.63	0.18
Income 25k-50k	−0.01	0.61	−0.19	−0.49	0.18	−0.36	−1.11	−0.44
Income 50k-75k	0.32	0.64	0.51	−0.02	−0.01	−0.01	0.17	0.41
Black	4.09	−21.64	−49.49	3.51	0.00	8.71	0.00	5.16
Hispanic	−2.86	−1.55	−3.64	0.77	−0.24	−1.65	4.84	0.00

Table 11: Format switching policy estimates - demographic dynamics