# Dynamic Product Positioning in Differentiated Product Markets: 

The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry A. Sweeting (Econometrica, 2013)

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## Motivation

- Performance Rights Act (2009): music radio stations should pay for musical performance rights
- Goal: develop and estimate a dynamic discrete-choice model of format choice to predict how much format variety would change if fees of $10 \%$ or $20 \%$ of revenues were introduced
- Static models to predict how specific policy-interventions or mergers would affect product characteristics: Fan (2012), Nishida (2012), and Datta and Sudhir (2012)
- Dynamic model to understand the benefits and costs of radio mergers: Jeziorski (2013)


## Empirical regularities

Data: 102 local radio markets from 2002-2005 (BIAfn; BIA
Financial Network (2006))

- Listeners with different demographic characteristics have different tastes. Music stations have higher audience shares
- Advertisers have different values on listeners with different demographics
- Only one station permanently closes, and 55 stations begin operating
- The average owner in a market operates 2.5 stations with some clustering in the same format


## Model

## Setup

- Radio station owners (firms) $o=1, \ldots, O_{m}$ in each market $m$ play an infinite horizon game. Firm o owns a set of stations $S^{\circ}$, with $F=0,1, \ldots, 7$ discrete formats to choose from.
- Each station's quality consists of:
- Observed quality $X_{s t}$ with effects $\gamma^{s}$.
- Unobserved quality $\xi_{\text {st }}$, independent of observed quality, and evolving according to an $\operatorname{AR}(1)$ process:

$$
\begin{equation*}
\xi_{s t}=\rho \xi_{s t-1}+v_{s t}^{\xi}+\gamma^{\xi} \cdot \mathbb{1}_{\left\{F_{s t} \neq F_{s t+1}\right\}} \tag{1}
\end{equation*}
$$

- Firms generate revenues by selling their audiences to advertisers. The audience is determined by a static discrete choice random coefficients logit model:

$$
\begin{equation*}
u_{i s t}=\gamma_{i}^{R}+X_{s t} \gamma^{s}+F_{s t}\left(\overline{\gamma^{F}}+\gamma_{D}^{F} D_{i}\right)+\xi_{s t}+\epsilon_{i s t}^{L} \tag{2}
\end{equation*}
$$

and the advertising revenue for a listener with demographics $D_{d}$ is determined by $r_{s t}\left(D_{d}\right)=\gamma_{m}\left(1+Y_{s t} \gamma^{Y}\right)\left(1+D_{d} \gamma_{d}\right)$

## Model

## Timing and Flow Profit Functions

- Each firm o observes the publicly observed state $M_{j, o, t}$, and pays fixed costs reduced by $C\left(M_{j, o, t}\right) \theta^{C}$ for operating multiple stations in the same formats
- Each firm o observes its $\epsilon_{o t}$, distributed Type 1 extreme value and scaled by $\theta^{\epsilon}$, and makes format choice $a_{o t} \in A_{\circ}\left(M_{j, o, t}\right)$
- Each firm o receives advertising revenues $\sum_{s \in S^{\circ}} R_{s}\left(M_{j, o, t} \mid \gamma\right)$, pays repositioning costs $W_{o}\left(a_{o t}\right) \theta^{W}$ and receives $\theta^{\epsilon} \epsilon_{o t}\left(a_{o t}\right)$
Define a firm's flow payoff as:

$$
\begin{align*}
& \pi_{o t}\left(a_{o t}, M_{j, o, t}, \theta, \gamma\right)+\theta^{\epsilon} \epsilon_{o t}\left(a_{o t}\right) \\
& =\underbrace{\sum_{s \in S^{\circ}} R_{s}\left(M_{j, o, t}, \gamma\right)}+\underbrace{\beta C\left(M_{j, o, t}\right) \theta^{C}}_{\text {fixed cost saving next period }}-\underbrace{W_{o}\left(a_{o t}\right) \theta^{W}}_{\text {repositioning costs }}+\underbrace{\theta^{\epsilon} \epsilon_{o t}\left(a_{o t}\right)}_{\text {payoff shock }} \tag{3}
\end{align*}
$$

advertising revenues

## Model

## Value Functions and Equilibrium Concept

Firms are assumed to use stationary Markov Perfect Nash Equilibrium in pure strategies

$$
\begin{array}{r}
V_{o}^{\Gamma}\left(M_{j, o, t}, \epsilon_{o t}\right)=\max _{a \in A_{o}\left(M_{j, o, t}\right)}\left\{\pi\left(a, M_{j, o, t}\right)+\theta^{\epsilon} \epsilon_{o t}(a)\right. \\
\left.+\beta \int V_{o}^{\Gamma}\left(M_{j, o, t+1}\right) f\left(M_{j, o, t+1} \mid a, \Gamma_{-o}, M_{j, o, t}\right) d M_{j, o, t+1}\right\}
\end{array}
$$

Given the distribution of payoff shocks, the CCPs are:

$$
\begin{equation*}
P^{\Gamma_{o}}\left(a, M_{j, o, t}, \Gamma_{-o}\right)=\frac{\exp \left(\frac{v_{o}^{\Gamma}\left(a, M_{j, o, t}, \Gamma_{-o}\right)}{\theta^{\epsilon}}\right)}{\sum_{a^{\prime} \in A_{o}\left(M_{j, o, t}\right)} \exp \left(\frac{v_{o}^{\Gamma}\left(a^{\prime}, M_{j, o, t}, \Gamma_{-o}\right)}{\theta^{\epsilon}}\right)} \tag{4}
\end{equation*}
$$

## Identification

Identification of Primitives

- Demand: Random Coefficient Logit Model:

$$
u_{i s t}=\gamma_{i}^{R}+X_{s t} \gamma^{s}+F_{s t}\left(\overline{\gamma^{F}}+\gamma_{D}^{F} D_{i}\right)+\xi_{s t}+\epsilon_{i s t}^{L}
$$

37 moment restrictions for 37 parameters

- Revenues:

$$
r_{s t}\left(D_{d}\right)=\gamma_{m}+\gamma_{m} \gamma_{d} D_{d}+\gamma_{m} \gamma^{Y} Y_{s t}+\gamma_{m} \gamma^{Y} Y_{s t} D_{d} \gamma_{d}
$$

- Demographic transition:

$$
\log \left(\frac{\text { pop }_{m e t}}{\text { pop } p_{m e t-1}}\right)=\tau_{0}+\tau_{1} \log \left(\frac{\text { pop }_{m e t-1}}{\text { pop }} \text { met-2 }\right)+u_{m e t}
$$

## Identification

## Identification of Primitives

- Normalization: $\pi=0$ for "temporarily off-air format"
- Initial Choice Probabilities:

$$
P_{o}^{i}\left(a \mid \mathcal{M}_{j o t}\right)=\frac{\exp \left(\frac{v_{0}^{\Gamma}\left(a, \mathcal{M}_{j o t}, \Gamma_{-0}\right)}{\theta^{\varepsilon}}\right)}{\sum_{a^{\prime} \in \mathcal{A}_{o}\left(\mathcal{M}_{j o t}\right)} \exp \left(\frac{v_{0}^{\Gamma}\left(a^{\prime}, \mathcal{M}_{j o t}, \Gamma_{-0}\right)}{\theta^{\varepsilon}}\right)}
$$

- Payoffs:

$$
\begin{aligned}
& \pi_{o t}\left(a_{o t}, M_{j, o, t}, \theta, \gamma\right)+\theta^{\epsilon} \epsilon_{o t}\left(a_{o t}\right) \\
& =\sum_{s \in S^{\circ}} R_{s}\left(M_{j, o, t}, \gamma\right)+\beta C\left(M_{j, o, t}\right) \theta^{C}-W_{o}\left(a_{o t}\right) \theta^{W}+\theta^{\epsilon} \epsilon_{o t}\left(a_{o t}\right)
\end{aligned}
$$

- $\theta^{\varepsilon}$ is identified since revenues are treated as observable


## Identification

## Identification of Counterfactuals

- Systematic part of the payoff:

$$
\begin{array}{r}
\tilde{\pi}\left(P_{o}^{i}\left(\mathcal{M}_{j o t}\right), \theta^{i}\right)=\sum_{s \in S^{\circ}} R_{s}\left(\mathcal{M}_{j o t} \mid \gamma\right)+\sum_{a \in \mathcal{A}_{o}\left(\mathcal{M}_{j o t}\right)} P_{o}^{i}\left(a \mid \mathcal{M}_{j o t}\right) \times \\
\left(\beta C_{o}(a) \theta^{C i}-W_{o}(a) \theta^{W i}+\theta^{\varepsilon i}\left(\varkappa-\log \left(P_{o}^{i}\left(a \mid \mathcal{M}_{j o t}\right)\right)\right)\right.
\end{array}
$$

where $\varkappa$ is Euler constant

- depends only on CCPs, so, it is identified (Hotz-Miller invertion theorem)
- Aguirregabiria (2005):

Counterfactual optimal choice probabilities are identified if (1) the discount factor, (2) the distribution of unobservables, (3) the flow payoff differences are also known

## Estimation

Step 1: Estimate $\gamma$ and $\xi$

- Random-coefficient demand model (GMM to avoid potential endogeneity) $\Rightarrow$ infer $\xi$ by Berry and Nevo algorithm
- Revenue function (NLLS)
- Firm's initial CCP's (multinomial logit)
- Demographics transition process (2SLS)

Step 2: Estimate $\theta$

- Value Function approximation (parametric and forward simulation)
value functions are approximated by a linear function of K functions $(\phi)$ of a specific set of N states:

$$
V_{o}^{P}\left(M_{j, o, t}\right) \simeq \sum_{k=1}^{K} \lambda_{k} \phi_{k o}\left(M_{j, o, t}\right)
$$

## Estimation

Step 2 1. Compute payoffs from $\gamma$, CCPs and current guess of $\theta$ :

$$
\begin{array}{r}
\tilde{\pi}\left(P_{o}^{i}\left(\mathcal{M}_{j o t}\right), \theta^{i}\right)=\sum_{s \in S^{\circ}} R_{s}\left(\mathcal{M}_{j o t} \mid \gamma\right)+\sum_{a \in \mathcal{A}_{o}\left(\mathcal{M}_{j o t}\right)} P_{o}^{i}\left(a \mid \mathcal{M}_{j o t}\right) \times \\
\left(\beta C_{o}(a) \theta^{C i}-W_{o}(a) \theta^{W i}+\theta^{\varepsilon i}\left(\varkappa-\log \left(P_{o}^{i}\left(a \mid \mathcal{M}_{j o t}\right)\right)\right)\right.
\end{array}
$$

2. Compute parameters of approximation $\lambda$
3. Use $\lambda$ to get future value of each firm when it chooses a
4. Estimate $\theta^{\prime}$ by MLE

$$
P_{o}^{i}\left(a \mid \mathcal{M}_{j o t}\right)=\frac{\exp \left(\frac{F V\left(a, \mathcal{M}_{j o t}, P_{o}^{i}\right)-W_{o}(a) \theta^{W}+\beta C_{o}(a) \theta^{C}}{\theta^{\varepsilon}}\right)}{\sum_{a^{\prime} \in \mathcal{A}_{o}\left(\mathcal{M}_{j o t}\right)} \exp \left(\frac{F V\left(a^{\prime}, \mathcal{M}_{j o t}, P_{o}^{i}\right)-W_{o}\left(a^{\prime}\right) \theta^{W}+\beta C_{o}(a) \theta^{C}}{\theta^{\varepsilon}}\right)}
$$

5. Use $\theta^{\prime}$ to update CCPs

## Asymptotics

Step 1: Estimate $\gamma$ and $\xi$

- Listener demand: (random coeeficient model estimated by GMM) consistent and converges with $\sqrt{N}$ under standrd assumptions
- Revenue function (NLLS), Demographics (2SLS) are consistent and converges with $\sqrt{N}$
- CCP's are estimated by MLE (multinomial logit): estimates are consistent; rate of convergence is $\sqrt{N}$ (CLT holds)

Step 2: Estimate $\theta$

- Value function approximation:

PMLE gives consistent and $\sqrt{N}$-converging estimates for $\theta$ (Aguirregabiria and Mira, 2007) if CCPs estimates are consistent and $\sqrt{N}$-converging.

- Standard errors are calculated using a bootstrap
- Estimates are more efficient since outside information is used


## Results

- Dynamic discreet-choice model of a format choice allowing for
- vertical and horizontal differentiation
- heterogenous customers' tastes and their different values to the advertisers
- multi-station ownership
- after 20 years:
- $\mathbf{1 0 \%}$ fees reduce the number of music stations by $\mathbf{9 . 4 \%}$ (music listening falls by 6.3\%)
- $\mathbf{2 0 \%}$ fees reduce the number of music stations by $\mathbf{2 0 \%}$ (music listening falls by 13.4\%)
- Not as dramatic decline as predicted: many valuable listeners prefer music programming to non-music one
- Long-run adjustment takes place pretty quickly: for both $10 \%$ and $20 \%$ fee, at least $40 \%$ of long-run change in the number of stations is completed within 2.5 years


## Summary

- What determines product variety: Borenstein and Netz (2002), George and Waldfogel (2003), Watson (2009) $\Rightarrow$ natural model for oligopoly
- radio industry: Berry and Waldfogel (2001) and Sweeting (2010).
- Static structural models predicting how policy-interventions or mergers affect product characteristics: Fan (2012), Nishida (2012), and Datta and Sudhir (2012) $\Rightarrow$ dynamic model with non-immediate adjustment (effect and speed of adjustment)
- Justified implementation of either value function approximation method for large state spaces required for studying an industry's evolution

