Estimation of cost efficiencies from mergers: Application to U.S. radio

Online Appendix

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1 Details of the static model

The radio industry is composed of geographical markets based on stations' overlapping signal contours. Suppose there are M such markets and that the payoff-relevant market characteristics at time t for market m are fully characterized by a set of covariates $d^{mt} \in \mathcal{D}$ (demand shifters). In each market m, there are up to K_m operating firms and up to J_m active products (to simplify the exposition, I omit the market subscripts in the rest of the paper). The set of products is equivalent to a set of available broadcast frequencies. The set of available frequencies rarely changes over time, and is fixed in the remainder of the paper. Each frequency has an assigned owner and might contain active or inactive radio station. Both types of stations can be traded (trades of stations are equivalent to trading frequencies), and the owner can decide to activate an inactive frequency and vice-versa.

Let $o_j \in K$ be the owner of the product j. I assume each product $j \in J$ is characterized by a triple $s_j^t = (f_j^t, \xi_j^t, o_j^t)$. The term $f_j^t \in F$ is a discrete characteristic of a station that describes a type of broadcast content, and $\xi_j^t \in \Xi$ is a continuous measure of programming quality that is unobserved to the econometrician. The state of the industry at the beginning of each period is, therefore, a pair $(s^t, d^t) \in \mathcal{S} \times \mathcal{D}$, where $s^t = \{s_1^t, \ldots, s_J^t\}$.

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1.1 Listeners

I assume each listener chooses only one radio station to listen to, at a particular moment. Suppose s is a set of active stations in the current market at a particular time. For any radio station j, I define a vector $\iota_j = (0, \ldots, 1, \ldots, 0)$, where 1 is placed in a position that indicates the format of station j.

The utility of listener i listening to station $j \in s$ is given by

$$u_{ij} = \theta^L_{1i}\iota_j - \theta^L_{2i}q_j + \theta^L_3 \mathrm{FM}_j + \xi_j + \epsilon_{ji}, \tag{1.1}$$

where θ^L_{2i} is the individual listener's demand sensitivity to advertising, q_j is the amount of advertising, ξ_j is the unobserved station quality, ϵ_{ji} is an unobserved preference shock (distributed type-1 extreme value), and θ^L_{1i} is a vector of the individual listener's random effects representing preferences for formats.

I assume the random coefficients can be decomposed as

$$\theta^L_{1i} = \theta^L_1 + \Pi D_i + \nu_{1i}, \quad D_i \sim F_m(D_i|d), \quad \nu_{1i} \sim N(0, \Sigma_1)$$

and

$$\theta^L_{2i} = \theta^L_2 + \nu_{2i}, \quad \nu_{2i} \sim N(0, \Sigma_2),$$

where Σ_1 is a diagonal matrix, $F_m(D_i|d)$ is an empirical distribution of demographic characteristics, ν_i is unobserved taste shock, and Π is the matrix representing the correlation between demographic characteristics and format preferences. I assume draws for ν_i are uncorrelated across time and markets.

The random effects model allows for fairly flexible substitution patterns. For example, if a particular rock station increases its level of advertising, the model allows consumers to switch proportionally to other rock stations, depending on demographics.

Following Berry, Levinsohn, and Pakes (1995), I can decompose the utility into a part that does not vary with consumer characteristics

$$\delta_j = \delta(q_j|\iota_j, \xi_j, \theta^L) = \theta^L_1\iota_i - \theta^L_2 q_j + \theta^L_3 \mathrm{FM}_j + \xi_j,$$

an interaction part

$$\mu_{ji} = \mu(\iota_j, q_j, \Pi D_i, \nu_i) = (\Pi D_i + \nu_{1i})\iota_j + \nu_{2i}q_j,$$

and error term ϵ_{ji}.

Given this specification, and the fact that ϵ_{ji} is distributed as an extreme value, one can derive the expected station rating, conditional on a vector of advertising levels q, market structure s, a vector of unobserved station characteristics ξ, and market demographic characteristics d,

$$r_j(q|s,\xi,d,\theta^L) = \int\int \frac{\exp[\delta_j + \mu_{ji}]}{\sum_{j'} \exp[\delta_{j'} + \mu_{j'i}]} dF(\nu_i) dF_m(D_i|d).$$

1.2 Advertisers

In this subsection, I present the details of the demand for advertising. The model captures several important features specific to the radio industry. In particular, the pricing is done on a per-listener basis, so that the price for a 60-second slot is a product of cost-per-point (CPP) and station rating (market share in percentages). Moreover, because radio stations have direct market power over advertisers, CPP is a decreasing function of the ad quantities sold by a station and its competitors. The simplest model that captures these features is a linear inverse demand for advertising expressed per listener, such as

$$p_j = \theta_1^A \left(1 - \theta_2^A \sum_{f' \in \mathbb{F}} \omega_{ff'}^m q_{f'}\right), \tag{1.2}$$

where f is a format of station j, θ_1^A is a scaling factor for the value of advertising, θ_2^A is a market power indicator, and $\omega_{ff'} \in \Omega$ are weights indicating competition closeness between formats f and f'.

The weights ω are a key factor determining competition between formats and thus market power. Different weights reflect the fact that some formats are further and others are closer substitutes for advertisers, because of differences in the demographic composition of their listeners. In principle, one could proceed by estimating these weights from the data. However, such estimation is not feasible because the available data do not contain radio station-level advertising prices. Instead, I make additional assumptions that will enable me to compute the weights using publicly available data. The remainder of this subsection discusses the formula for the weights and provides an example supporting this intuition.

Let there be $\mathcal{A}$ types of advertisers. Each type $a \in \mathcal{A}$ targets a certain demographic group(s) a; that is, an advertiser of type a gets positive utility only if a listener of type a hears an ad. Denote $r_{f|a}$ to be the probability that a listener of type a chooses format f, and $r_{a|f}$ to be the probability that a random listener of format f is of type a. Advertisers take these numbers, along with station ratings r_j, as given and decide on which station to advertise. This assumption is motivated by the fact that about 75% of ads are purchased by small local firms. Such firms' advertising decisions are unlikely to influence prices and station ratings in the short run.

This decision problem results in an inverse demand for advertising with weights $\omega_{jj'}$, which are given by

$$\omega_{ff'} = \frac{1}{\sum_{a\in\mathcal{A}} r^2_{a|f}} \sum_{a\in\mathcal{A}} r_{a|f}\left(r_{a|f} r_{f'|a}\right). \tag{1.3}$$

The intuition behind this equation is that the total impact on the per-listener price of an ad in format f is a weighted average of the impacts on the per-listener value of an ad for different types of advertisers. The weighting uses the conditional probabilities of advertisers' arrivals, which are equal to the conditional probability of listeners' arrivals $r_{a|f}$. For each advertiser of type a, the change in value of an ad in format f, in response to a change in total quantity supplied in format f', is affected by two things: the change is proportional to the probability of correct targeting in format f, given by $r_{a|f}$, because advertisers are expected utility maximizers; and it is proportional to the share of advertising purchased by this advertiser in format f', given by $r_{f'|a}$. Assembling these pieces together and normalizing the weights to sum to 1 gives equation (1.3). Extensive discussions with examples of the weights as well as micro foundations for the model can be found in Jeziorski (2013).

In the next section, I will combine demand for programming and advertising to compose the profits of the radio station owners.

1.3 Radio station owners

In this subsection. I will describe a profit-maximizing problem for the radio station owners. Given the advertising quantity choices of competing owners q_{-k}, the profit of radio station owner k is given by

$$\begin{aligned}\bar{\pi}_k(q_k|q_{-k},\xi,\theta) &= \max_{\{q_j:o_j=k\}} \sum_{\{j:o_j=k\}} r_j(q|\xi,\theta^L)p_j q_j - \mathrm{MC}_j(q_j) = \\ &= \theta_1^A \max_{\{q_j:o_j=k\}} \sum_{\{j:o_j=k\}} q_j r_j(q|\xi,\theta^L)\left(1-\theta_2^A \sum_{f'\in\mathbb{F}} \omega^m_{ff'} q_{f'}\right) + \mathrm{C}_j(q_j|\theta^A,\theta^C),\end{aligned} \tag{1.4}$$

where $C_j(q_j)$ is the total cost of selling advertising. I assume constant marginal cost and allow for a firm level of unobserved cost heterogeneity η_j; that is, $\mathrm{C}_j(q_j|\theta^A,\theta^C) = \theta_1^A[\theta^C+\eta_j]q_j$.

I assume the markets are in a Cournot Nash Equilibrium. The first-order conditions for profit optimization become

$$r_j p_j + \sum_{\{j':o_{j'}=k\}} q_{j'} \left[\frac{\partial r_{j'}}{\partial q_j} p_{j'} - r_{j'} \theta_2^A \omega_{jj'}^m \right] - \theta^C - \eta_j = 0 \quad \forall k \text{ and } j \in \{j : o_j = k\}. \tag{1.5}$$

Additionally, I assume station unobserved quality is exogenous but serially correlated. It evolves according to an AR(1) process such that

$$\xi_j^t = \rho \xi_j^{t-1} + \zeta_j^t, \tag{1.6}$$

where ζ_j^t is an exogenous innovation to station quality.

1.4 Estimation

I perform estimation of the model in two steps. In the first step, I estimate the demand model that includes parameters of the consumer utility θ^L (see equation (1.1)) and the unobserved station quality lag parameter ρ (see equation (1.6)). In the second step, I recover parameters of the inverse demand for advertising θ^A, $w_{jj'}$ (see equation (1.2)), and cost parameters θ^C (see equation (1.4)).

The first stage provides the estimates of demand for radio programming θ^L. I perform this estimation using the generalized method of simulated moments. I use two sets of moment conditions. The first set is based on the fact that innovation to a station's unobserved quality ξ_j has a mean of zero, conditional on the instruments:

$$E[\xi_{jt} - \rho \xi_{jt-1} | Z_1, \theta^L] = 0. \tag{1.7}$$

This moment condition follows Berry, Levinsohn, and Pakes (1995) and extends their work by explicitly introducing auto-correlation of ξ. I use instruments for advertising quantity, because it is likely to be correlated with unobserved station quality. My instruments include: lagged mean and second central moment of competitors' advertising quantity, lagged market HHIs, and lagged number and cumulative market share of other stations in the same format. These instruments are valid under the assumption that ξ_t follows an AR(1) process and the by fact that the decisions about portfolio selection are made before decisions about advertising.

A second set of moment conditions is based on demographic listenership data. Let R_{fc} be the national market share of format f among listeners possessing certain demographic characteristics c. The population moment conditions are

$$\int_t \int_{(D_{ic}^t, m)} \int_{\nu_i} \frac{\exp[\delta_j^{mt} + \mu_{ji}^{mt}]}{\sum_{j'} \exp[\delta_{j'}^{mt} + \mu_{ij'}^{mt}]} dF(\nu_i) dF_c^t(D_{ic}^t, m) dt = R_{fc}, \tag{1.8}$$

where $F_c^t(D_i, m)$ is a national distribution of people who possess characteristic c at time t. Each person is characterized by the demographic characteristics D_i and the market m to which they belong.

For each time t and demographic characteristic c, I draw $\mathcal{I}$ observation pairs (D_{ic}^t, m) from the nationally aggregated CPS. Let $g = (g_1, g_2)$ represent the empirical moments and W be a weighting matrix. I estimate the model by using the constrained optimization procedure:

$$\min_{\theta^L, \xi, g} g' W g,$$

subject to

$$\begin{aligned}
&\hat{r}_{jmt}(q_{mt}|s_{mt}, \xi_{mt}, d_{mt}, \theta^L) = r_{jmt} \quad \forall t, m \\
&\frac{1}{\mathcal{T}\mathcal{I}} \sum_t \sum_{(D_{ic}^t, m)} \int_{\nu_i} \frac{\exp[\delta_j^{mt} + \mu_{ji}^{mt}]}{\sum_{j'} \exp[\delta_{j'}^{mt} + \mu_{ij'}^{mt}]} dF(\nu_i) - R_{fc} = g_1 \quad \forall c \\
&\frac{1}{\text{size of } \xi} Z_1(\xi - \rho L \xi) = g_2,
\end{aligned} \tag{1.9}$$

where L is a lag operator that converts the vector ξ into one-period lagged values. If the radio station did not exist in the previous period, the lag operator has a value of zero. Integration with respect to demographics when calculating the first constraint is obtained by drawing from the CPS in the particular market and period. This way of integrating allows us to maintain proper correlations between possessed demographic characteristics. The same is true when obtaining the data set D_{ict}. When computing the interaction terms μ in the second constraint, I draw one vector ν_i from the normal distribution for each D_{ict}.

The second stage of the estimation obtains the competition matrix Ω and the parameters of demand for advertising θ^A. I perform the estimation separately for every market, thereby allowing for different Ω and θ^A.

To compute the matrices Ω^m for each market, I use the specification laid out in section 1.2. The elements of the matrix Ω are specified as

$$\omega_{ff'} = \frac{1}{\sum_{a \in \mathcal{A}} r_{a|f}^2} \sum_{a \in \mathcal{A}} r_{a|f} \left(r_{a|f} r_{f'|a} \right)$$

following equation (1.3). The $r_{f|a}$ are advertisers' beliefs about listeners' preferences for formats and are constant across markets. To recognize that advertisers know the demographic composition of each market, I allow for market-specific conditional probabilities of listeners' arrival for each format $r_{f|a}^m$. However, I assume the advertisers compute those values by using Radio Today reports and the Current Population Survey. After computing weights, I treat Ω^m as exogenous and fixed in all of the following steps.[1]

After computing matrices Ω, I estimate θ^A. Using estimates of demand for radio programming θ^L from the first stage, I compute ratings for each station conditioned on the counterfactual advertising quantities. I use the set of $3M$ moment conditions

$$E_m[\eta^m | Z_2, \theta^A, \theta^C] = 0 \quad \forall m \in \mathbf{M}, \tag{1.10}$$

where the integral is taken with respect to time and stations in each market. η_j^{tm} is an unobserved shock to marginal cost defined in equation (1.2). The Z_2 are three instruments: a column of ones, the AM/FM dummy, and the number of competitors in the same format. They are uncorrelated with η^m under the IID assumption, but are correlated with the current choice of quantity because they describe the market structure.

I back out η_j^{tm} using FOCs for owner's profit maximization (see equation (1.4));

$$\eta_j^t = r_j^t p_j^t + \sum_{\{j' : o_{j'}^{tm} = k\}} q_{j'}^t \left[\frac{\partial r_{j'}^t}{\partial q_j^t} p_{j'}^t - \theta_{2m}^A r_{j'}^t \omega_{ff'}^m \right] - \theta_m^C \quad \forall t \in \mathbf{T}, k \in \mathbf{K}^{tm}, j \in \{j' : o_{j'}^{tm} = k\}, \tag{1.11}$$

Because the equation does not depend on θ_{1m}^A, I can use it to estimate θ_{2m}^A and θ_m^C. During the estimation, I allow for a different value of marginal cost for each market. I allow for three different values for the slope of inverse demand, depending on the population of the market (up to 500 people, between 500 and 1500, and 1500 or more). Using the estimates of θ^L and ξ from the first stage, I calculate ratings and derivatives of ratings in the equation (1.11). Demographic draws are taken from the CPS and are independent of those used in the first stage. Given the estimates of θ_{2m}^A and θ^C, I can back out θ_{1m}^A by equating the observed average revenue in each market with its predicted counterpart.

Next I discuss a variation in the data that identifies parameters θ^A and θ^C. The intuition for such identification is that estimating equation 1.11 can be regarded as a linear regression in which θ_m^C is an intercept and θ_2^A is a coefficient of a variable that is a function of supplied quantity. In this case, the mean deviation of FOCs from zero in each market identifies the intercept θ_m^C. The slope parameter θ_2^A is identified by the size of the firm's response to changes in quantity supplied by its competitors due to change in the market structure or demographics. Such a response is

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[1] Such an approach potentially ignores possible variance of the Ω^m estimator. The source of this variance might come from the finiteness of the CPS data set and the distribution of Arbitron estimates.

composed of listeners' demand feedback and the direct effect of quantity on CPP. Elasticity of listeners' demand, which determines the strength of the feedback, is consistently estimated in the first step. Therefore, one can subtract the feedback effect from the total response observed in the data. As a result, I obtain the strength of the direct effect, which identifies the slope of the CPP, θ_2^A. For example, if we look at the response of ad quantity to the merger, the slope of listeners' demand alone predicts large increases in ad quantity. However, in the data, we observe smaller increases or even decreases in the quantity supplied, depending on the market. Those differences are rationalized by a negative value of CPP slope, θ_2^A.

1.5 Results

This section presents estimates of the structural parameters. The next subsection discusses listeners' demand parameters, followed by results concerning advertisers' demand and market power. The last subsection contains estimates of marginal cost and profit margin (before subtracting fixed cost).

1.6 Listeners' demand

Table 1 contains estimates of demand parameters for radio programming. The estimate of the mean effect of advertising on listeners' utility is negative and statistically significant. This finding is consistent with the belief that radio listeners have a disutility for advertising. Regarding the mean effects of programming formats, the Contemporary Hit Radio format gives the most utility, whereas the News/Talk format gives the least.

The second column of Table 1 contains variances of random effects for station formats. The higher a format's variance, the more persistent the tastes of that format's listeners. For example, in response to an increased amount of advertising, if the variance of the random effect for that format is high, listeners tend to switch to a station of the same format. The estimates also suggest tastes for the Alternative/Urban format are the most persistent.

Table 2 contains estimates of interactions between listener characteristics and format dummies. The majority of the parameters are consistent with intuition. For example, younger people are more willing to choose a CHR format, whereas older people go for News/Talk. The negative coefficients on the interaction of the Hispanic format with education and income suggest less educated Hispanic people with lower incomes are more willing to listen to Hispanic stations. For

	Mean Effects (θ_1^L)	Random Effects (Σ_1)
Advertising	-1.106 (0.002)	0.030 (0.009)
AM/FM	0.861 (0.000)	-
AC, SmoothJazz, and New AC	-2.431 (0.008)	0.043 (0.004)
Rock	-1.559 (0.140)	0.004 (0.020)
CHR	-0.179 (0.025)	0.009 (0.006)
Alternative Urban	-2.339 (0.026)	0.348 (0.008)
News/Talk	-4.678 (0.010)	0.024 (0.002)
Country	-2.301 (0.006)	0.011 (0.003)
Spanish	-1.619 (0.004)	0.011 (0.001)
Other	-4.657 (0.004)	0.005 (0.002)
ρ	0.568 (0.091)	-

Table 1: Estimates of mean and random effects of demand for radio programming.

Blacks, I find a disutility for Country, Rock, and Hispanic, and a high utility for Urban. This finding is consistent with the fact that Urban radio stations play mostly rap, hip-hop, and soul music performed by Black artists.

1.7 Advertisers' demand

Tables 5 presents the weights for selected markets representing large, medium, and small listener populations. They were computed using the 1999 edition of Radio Today publication and Common Population Survey aggregated from 1996 to 2006. I also compute a total impact coefficient that is the sum of all the columns of the table for each format. Not surprisingly, general interest formats such as AC and News/Talk have the biggest impact on the price of advertising, whereas the Spanish format has the smallest. The values on the diagonals of the matrices represent the formats' own

	Demographics characteristics (Π)					
	Age	Sex	Education	Income	Black	Spanish
AC, SmoothJazz, and New AC	−0.171 (0.001)	−0.341 (0.064)	0.602 (0.013)	−0.024 (0.003)	0.121 (0.012)	−1.014 (0.008)
Rock	−0.645 (0.072)	0.399 (0.031)	0.861 (0.006)	−0.147 (0.045)	−1.359 (0.007)	−1.643 (0.003)
CHR	−2.541 (0.015)	0.477 (0.080)	1.772 (0.006)	−0.291 (0.005)	1.946 (0.015)	0.463 (0.001)
Alternative Urban	−0.817 (0.008)	1.350 (0.018)	0.583 (0.025)	−0.141 (0.002)	3.152 (0.005)	0.267 (0.027)
News/Talk	0.329 (0.002)	1.228 (0.012)	0.237 (0.009)	0.093 (0.005)	−0.321 (0.001)	−1.649 (0.005)
Country	0.062 (0.004)	−0.149 (0.022)	0.133 (0.004)	−0.125 (0.003)	−1.548 (0.009)	−1.717 (0.002)
Spanish	−0.024 (0.013)	−0.908 (0.012)	−0.328 (0.018)	−1.140 (0.002)	−2.560 (0.004)	0.797 (0.003)
Other	0.263 (0.373)	0.624 (0.003)	0.338 (0.006)	−0.031 (0.063)	0.498 (0.001)	0.238 (0.002)

Table 2: Interaction terms between listeners' demographics and taste for radio programming.

Market population	less than .5m	between .5m and 1.5m	more than 1.5m
	1.34 (0.046)	0.35 (0.026)	0.00 (0.008)

Table 3: Slope of the inverse demand for ads θ_2^A, by market size.

effect of the quantity of advertising supplied on per-listener price. They are usually bigger than the off-diagonal values, which suggests ad quantity in the same format is a primary driver of a per-listener price. In line with intuition, the formats with the most demographically homogenous listener pools, Urban/Alternative and Spanish, have the highest values of own effects. On the other hand, general interest formats, such as CHR and Rock, are characterized by the smallest values of the own effect, measuring the fact that their target listener population is more dispersed across other formats. For cross effects, note that News/Talk is close to AC, and Urban is close to CHR. This finding can be explained, for example, by the age of the listeners. The formats appeal to an older population in the former case and to a younger population in the latter case.

Table 3 presents estimates of the slope of inverse demand. In markets with less than 0.5m people, radio stations have considerable control over per-listener price. However, such control drops significantly in markets with 0.5m to 2m people, and it disappears completely in markets with more than 2m people, making radio stations essentially price takers.

1.8 Supply

Table 4 presents the marginal costs of selling advertising minutes. The values of this cost range from \$356 per minute of advertising sold in Los Angeles, CA, to \$11 in Ft. Myers, FL. The variation in market population can explain 66% of the variation in marginal cost. A population increase of 1,000 translates to about a 2-cent increase in marginal cost (with t-stat equal to 12). The high correlation between population and marginal costs can be explained by the fact that revenues per minute of advertising are an increasing function of total market population.

From the revenues and marginal cost estimates, I can calculate variable profit margins, presented in the last column of Table 4. They range from 92% in Shreveport, LA, to 15% in Honolulu, HI, and Reno, NV. The marginal effect of an extra minute per day of broadcasted advertising translates into 0.6% extra profit margin.

Market	Population (mil)	Marginal cost ($ per-minute)	Profit margin	Market	Population	Marginal cost	Profit margin
Los Angeles, CA	13,155	356.4 (5.15)	30%	Tulsa, OK	856	72.8 (2.13)	21%
Chicago, IL	9,341	180.0 (2.70)	34%	Knoxville, TN	785	54.3 (1.99)	27%
Dallas-Ft. Worth, TX	5,847	198.6 (5.60)	28%	Albuquerque, NM	740	27.4 (1.04)	36%
Houston-Galveston, TX	5,279	199.7 (4.20)	28%	Ft. Myers-Naples-Marco Island, FL	737	11.3 (0.94)	57%
Atlanta, GA	4,710	95.4 (3.37)	43%	Omaha-Council Bluffs, NE-IA	728	48.0 (0.91)	28%
Boston, MA	4,532	172.2 (3.68)	33%	Harrisburg-Lebanon-Carlisle, PA	649	29.7 (1.44)	42%
Miami-Ft, FL	4,174	134.3 (3.70)	28%	El Paso, TX	619	41.8 (4.12)	20%
Seattle-Tacoma, WA	3,776	128.7 (2.21)	29%	Quad Cities, IA-IL	618	51.3 (1.30)	23%
Phoenix, AZ	3,638	63.7 (1.84)	39%	Wichita, KS	598	38.9 (0.85)	25%
Minneapolis-St. Paul, MN	3,155	160.8 (4.66)	26%	Little Rock, AR	577	45.2 (1.64)	26%
St. Louis, MO	2,689	190.6 (5.38)	18%	Columbia, SC	577	60.0 (2.10)	23%
Tampa-St, FL	2,649	102.7 (2.09)	26%	Charleston, SC	569	59.6 (1.74)	19%
Denver-Boulder, CO	2,604	99.9 (1.40)	32%	Des Moines, IA	564	21.3 (0.92)	40%
Portland, OR	2,352	48.6 (1.35)	41%	Spokane, WA	540	24.5 (0.63)	28%
Cleveland, OH	2,134	170.6 (3.34)	24%	Madison, WI	520	93.6 (3.02)	22%
Charlotte, NC-SC	2,127	67.1 (1.96)	38%	Augusta, GA	510	30.9 (0.60)	24%
Sacramento, CA	2,100	47.6 (1.30)	42%	Ft. Wayne, IN	509	37.8 (1.35)	27%
Salt Lake City, UT	1,924	58.1 (1.19)	26%	Lexington-Fayette, KY	495	36.8 (1.59)	35%
San Antonio, TX	1,900	75.0 (2.27)	24%	Chattanooga, TN	471	41.5 (2.53)	29%
Kansas City, MO-KS	1,871	152.5 (2.87)	19%	Boise, ID	469	46.2 (3.73)	30%
Las Vegas, NV	1,752	47.7 (1.49)	32%	Jackson, MS	453	18.6 (2.03)	59%
Milwaukee-Racine, WI	1,713	74.6 (1.27)	25%	Eugene-Springfield, OR	439	27.4 (1.29)	31%
Orlando, FL	1,686	42.4 (1.77)	41%	Reno, NV	400	99.7 (1.64)	15%
Columbus, OH	1,685	70.2 (1.53)	30%	Shreveport, LA	359	19.8 (4.25)	92%
Indianapolis, IN	1,602	86.8 (2.32)	26%	Fayetteville, NC	337	38.1 (2.48)	46%
Norfolk, VA	1,583	196.8 (4.64)	17%	Springfield, MA	336	20.8 (0.87)	55%
Nashville, TN	1,342	40.5 (1.84)	38%	Macon, GA	276	34.4 (2.29)	26%
Greensboro-Winston, NC	1,329	53.5 (2.34)	32%	Binghamton, NY	255	37.5 (1.51)	27%
New Orleans, LA	1,294	91.2 (2.44)	24%	Lubbock, TX	248	57.7 (1.98)	18%
Memphis, TN	1,278	53.2 (1.82)	30%	Odessa-Midland, TX	231	21.4 (0.99)	27%
Jacksonville, FL	1,271	66.1 (1.64)	29%	Fargo-Moorhead, ND-MN	200	48.6 (2.42)	25%
Oklahoma City, OK	1,268	75.6 (1.35)	25%	Medford-Ashland, OR	184	27.7 (0.90)	28%
Buffalo-Niagara Falls, NY	1,150	141.5 (3.63)	19%	Duluth-Superior, MN-WI	159	43.3 (0.79)	20%
Louisville, KY	1,100	92.9 (2.36)	21%	Parkersburg-Marietta, WV-OH	157	31.7 (1.41)	21%
Richmond, VA	1,066	55.3 (1.47)	28%	Abilene, TX	149	23.0 (1.14)	26%
Birmingham, AL	1,030	85.8 (2.50)	24%	Eau Claire, WI	149	31.6 (2.77)	28%
Honolulu, HI	938	78.2 (2.39)	15%	Williamsport, PA	130	31.0 (1.13)	23%
Albany, NY	909	113.9 (3.18)	16%	Monroe, LA	124	14.2 (1.49)	64%
Grand Junction, CO	902	24.5 (0.67)	24%	Sioux City, IA	118	26.1 (0.96)	24%
Tucson, AZ	870	41.1 (0.93)	27%	San Angelo, TX	104	26.4 (1.36)	16%
Grand Rapids, MI	864	37.9 (0.79)	38%	Bismarck, ND	99	32.8 (1.65)	22%

Table 4: Estimated marginal cost (in dollars per minute of broadcasted advertising) and profit margins (before subtracting the fixed cost) for a chosen set of markets.

Los Angeles, CA

	AC SmoothJazz New AC	Rock	CHR	Alternative Urban	News/Talk	Country	Spanish	Other
AC SmoothJazz New AC	**0.22**	0.10	0.11	0.09	0.17	0.14	0.00	0.17
Rock	0.15	**0.21**	0.12	0.09	0.16	0.13	0.01	0.12
CHR	0.18	0.12	**0.16**	0.16	0.10	0.13	0.03	0.13
Alternative Urban	0.11	0.05	0.17	**0.44**	0.06	0.05	0.00	0.12
News/Talk	0.17	0.10	0.05	0.05	**0.30**	0.13	0.00	0.21
Country	0.16	0.10	0.09	0.07	0.15	**0.22**	0.01	0.21
Spanish	0.03	0.04	0.11	0.02	0.01	0.03	**0.72**	0.04
Other	0.18	0.07	0.06	0.08	0.20	0.17	0.00	**0.23**
Total impact	1.20	0.79	0.87	0.99	1.15	1.00	0.77	1.23

Atlanta, GA

	AC SmoothJazz New AC	Rock	CHR	Alternative Urban	News/Talk	Country	Spanish	Other
AC SmoothJazz New AC	**0.20**	0.10	0.12	0.09	0.14	0.18	0.00	0.18
Rock	0.14	**0.21**	0.13	0.10	0.12	0.17	0.01	0.13
CHR	0.17	0.13	**0.17**	0.14	0.09	0.17	0.01	0.13
Alternative Urban	0.11	0.06	0.16	**0.40**	0.06	0.08	0.00	0.13
News/Talk	0.16	0.10	0.05	0.05	**0.25**	0.17	0.00	0.22
Country	0.15	0.09	0.08	0.06	0.13	**0.26**	0.01	0.22
Spanish	0.04	0.04	0.12	0.02	0.01	0.03	**0.71**	0.03
Other	0.16	0.07	0.06	0.07	0.16	0.23	0.01	**0.25**
Total impact	1.11	0.78	0.88	0.94	0.95	1.31	0.75	1.29

Knoxville, TN

	AC SmoothJazz New AC	Rock	CHR	Alternative Urban	News/Talk	Country	Spanish	Other
AC SmoothJazz New AC	**0.20**	0.11	0.16	0.11	0.10	0.16	0.01	0.16
Rock	0.13	**0.21**	0.14	0.11	0.10	0.18	0.01	0.12
CHR	0.16	0.12	**0.18**	0.14	0.08	0.17	0.02	0.13
Alternative Urban	0.12	0.06	0.16	**0.38**	0.06	0.08	0.00	0.13
News/Talk	0.16	0.13	0.10	0.09	**0.17**	0.16	0.01	0.18
Country	0.15	0.13	0.14	0.10	0.09	**0.22**	0.01	0.16
Spanish	0.05	0.05	0.11	0.02	0.02	0.04	**0.66**	0.05
Other	0.17	0.09	0.11	0.12	0.12	0.18	0.01	**0.21**
Total impact	1.12	0.90	1.11	1.05	0.74	1.21	0.72	1.14

Table 5: Product closeness matrices for chosen markets.

2 First-stage estimates not reported in the paper

	AC	Rock	CHR	Urban Alt.	News Talk	Country	Spanish	Other
Own AC	**−12.27***** (2.56)	−5.02** (2.42)	−10.21** (4.05)	−7.35** (3.77)	−10.32*** (2.31)	−8.25*** (2.38)	−68.00*** (11.81)	−22.65*** (2.50)
Own Rock	−6.55*** (2.41)	**−2.06** (2.71)	−14.09*** (4.73)	−8.01** (3.94)	−6.22*** (2.24)	−8.01*** (2.71)	−44.14*** (9.80)	−10.60*** (2.29)
Own CHR	−6.99* (3.69)	−3.68 (4.13)	**−17.26**** (7.69)	−5.87 (6.37)	−3.33 (3.50)	−10.99** (4.44)	−37.20*** (10.73)	−19.95*** (3.92)
Own Urban/Alt.	−10.74*** (3.13)	−10.66*** (3.51)	−6.82 (5.11)	**−1.90** (3.54)	−18.33*** (3.39)	−16.01*** (3.57)	−76.93*** (15.18)	−18.90*** (2.71)
Own News/Talk	−6.01*** (2.20)	−6.23** (2.54)	−1.11 (3.62)	−18.35*** (4.00)	**−9.08***** (2.47)	−7.19*** (2.38)	−61.68*** (8.30)	−19.62*** (2.38)
Own Country	−3.80* (2.27)	−5.82** (2.53)	−3.98 (3.80)	−19.13*** (4.49)	−13.45*** (2.59)	**−10.75***** (2.74)	−48.98*** (9.09)	−17.46*** (2.42)
Own Spanish	−17.65*** (4.44)	−24.90*** (6.64)	−20.49** (8.03)	−29.21*** (7.63)	−38.96*** (6.20)	−33.17*** (6.42)	**−13.93***** (3.38)	−43.45*** (5.47)
Own Other	−19.62*** (2.45)	−16.19*** (2.71)	−15.03*** (3.97)	−27.03*** (3.83)	−19.23*** (2.37)	−18.30*** (2.56)	−57.41*** (6.50)	**−23.55***** (2.25)
Top 2 comp. AC	**3.37***** (1.26)	−4.22** (1.69)	−2.35 (2.40)	−0.97 (2.22)	−0.12 (1.38)	2.40* (1.44)	7.03*** (2.39)	0.04 (1.18)
Top 2 comp. Rock	0.19 (1.54)	**−1.25** (1.72)	−1.54 (2.59)	−1.19 (2.56)	−2.49 (1.62)	1.01 (1.65)	−1.91 (2.59)	1.20 (1.38)
Top 2 comp. CHR	0.62 (1.85)	3.15 (2.29)	**−1.01** (2.81)	2.33 (3.02)	−2.52 (1.94)	4.25** (2.14)	1.25 (3.40)	0.52 (1.58)
Top 2 comp. Urban/Alt.	−1.17 (1.93)	−2.94 (2.29)	−8.21** (3.78)	**−3.94*** (2.33)	−3.00 (1.92)	−1.60 (2.07)	1.87 (3.11)	−2.67* (1.53)
Top 2 comp. News/Talk	−2.35* (1.33)	2.53* (1.54)	0.15 (2.34)	0.94 (1.95)	**3.05**** (1.31)	0.17 (1.41)	−5.60** (2.35)	2.05* (1.17)
Top 2 comp. Country	2.41* (1.36)	−0.78 (1.58)	1.11 (2.21)	−0.69 (2.31)	4.89*** (1.30)	**1.54** (1.37)	11.84*** (2.49)	0.88 (1.18)
Top 2 comp. Spanish	3.09 (2.68)	2.07 (3.52)	−11.44* (6.33)	0.45 (4.04)	4.55** (2.30)	−4.25 (3.58)	**2.53** (2.28)	0.65 (2.31)
Top 2 comp. Other	−1.30 (1.34)	2.64* (1.53)	2.36 (2.24)	2.17 (1.97)	−1.35 (1.35)	−0.58 (1.45)	5.23** (2.47)	**5.15***** (1.03)

Standard errors (corrected for sequential estimation) in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Estimates of acquisition strategy: impact of portfolios of the player and top 2 competitors on an acquisition decision in a particular format. The portfolio variables are measured as the number of owned stations of the particular format divided by the total number of stations in the market.

	AC	Rock	CHR	Urban Alt.	News Talk	Country	Spanish	Other
AM	-1.54^{***} (0.31)	-3.11^{***} (0.43)	-3.04^{***} (0.47)	-1.84^{***} (0.35)	1.60^{***} (0.31)	-1.05^{***} (0.34)	0.03 (0.32)	−0.07 (0.30)
AC	$\mathbf{6.71}^{***}$ (0.51)	1.58^{***} (0.54)	1.78^{***} (0.55)	1.69^{***} (0.55)	0.13 (0.55)	1.19^{**} (0.55)	1.18^{**} (0.57)	2.45^{***} (0.51)
Rock	2.78^{***} (0.69)	$\mathbf{7.12}^{***}$ (0.69)	0.96 (0.75)	2.81^{***} (0.71)	0.55 (0.72)	1.32^{*} (0.73)	1.30^{*} (0.77)	2.81^{***} (0.69)
CHR	2.15^{***} (0.66)	1.22^{*} (0.70)	$\mathbf{6.67}^{***}$ (0.67)	2.36^{***} (0.68)	−0.93 (0.77)	0.07 (0.77)	1.42^{*} (0.73)	1.98^{***} (0.67)
Urban Alt.	1.59^{***} (0.57)	1.90^{***} (0.58)	0.86 (0.62)	$\mathbf{6.34}^{***}$ (0.56)	−0.29 (0.60)	0.22 (0.64)	0.86 (0.64)	1.99^{***} (0.55)
News Talk	1.27^{**} (0.54)	0.59 (0.65)	0.41 (0.68)	0.35 (0.66)	$\mathbf{5.68}^{***}$ (0.54)	0.81 (0.57)	1.00^{*} (0.57)	1.36^{***} (0.52)
Country	1.60^{***} (0.50)	1.09^{**} (0.52)	0.70 (0.55)	0.98^{*} (0.56)	0.11 (0.51)	$\mathbf{6.49}^{***}$ (0.49)	1.12^{**} (0.55)	1.59^{***} (0.49)
Spanish	0.84 (0.60)	−1.56 (1.13)	0.31 (0.66)	0.61 (0.63)	−0.34 (0.53)	0.37 (0.63)	$\mathbf{5.10}^{***}$ (0.53)	1.24^{**} (0.51)
Other	2.82^{***} (0.45)	1.76^{***} (0.48)	0.99^{*} (0.52)	2.07^{***} (0.48)	0.49 (0.47)	1.38^{***} (0.48)	1.37^{***} (0.50)	$\mathbf{6.69}^{***}$ (0.44)
Dark	-1.81^{***} (0.51)	-2.38^{***} (0.59)	-3.55^{***} (0.61)	-3.34^{***} (0.55)	-3.49^{***} (0.57)	-1.99^{***} (0.59)	-2.74^{***} (0.47)	-1.62^{***} (0.46)

Standard errors (corrected for sequential estimation) in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Format-switching-strategy estimates: choice-specific past format dummies.

	AC	Rock	CHR	Urban Alt.	News Talk	Country	Spanish	Other
Own AC	**−0.10** (4.72)	8.28* (4.88)	2.17 (5.09)	4.49 (5.03)	5.16 (4.75)	6.53 (4.87)	−0.72 (5.45)	−0.29 (4.67)
Own Rock	1.70 (4.80)	**−1.87** (4.93)	8.58* (5.16)	0.61 (5.16)	3.61 (4.84)	1.19 (4.98)	−8.06 (5.81)	−2.66 (4.74)
Own CHR	−2.59 (6.20)	−3.20 (6.52)	**−15.52**** (6.74)	−1.78 (6.79)	4.08 (6.23)	−1.79 (6.42)	−12.38* (7.50)	−11.40* (6.13)
Own Urban/Alt.	1.15 (5.06)	−0.59 (5.36)	3.01 (5.66)	**2.95** (5.24)	1.16 (5.15)	0.97 (5.41)	−7.58 (6.71)	−0.76 (4.88)
Own News/Talk	11.79** (5.03)	10.45** (5.17)	13.20** (5.27)	5.02 (5.28)	**8.38*** (5.08)	11.06** (5.18)	4.33 (5.79)	8.17 (5.00)
Own Country	−0.10 (4.48)	4.49 (4.65)	4.05 (4.83)	−7.81 (5.02)	0.13 (4.52)	**−2.21** (4.55)	−4.70 (5.48)	0.77 (4.41)
Own Spanish	−11.55** (5.43)	0.32 (5.91)	4.58 (5.63)	−5.63 (5.75)	−5.84 (5.25)	−10.12* (5.97)	**15.08***** (4.40)	−4.11 (4.93)
Own Other	−4.03 (3.45)	−4.27 (3.62)	−3.84 (3.84)	−2.83 (3.80)	−1.47 (3.53)	−3.31 (3.60)	−9.04** (4.15)	**−2.56** (3.34)
Own Dark	−0.53 (0.37)	−0.55 (0.43)	0.16 (0.36)	0.27 (0.30)	−0.46 (0.42)	−0.60 (0.45)	−0.02 (0.24)	−0.53 (0.33)
Top 2 comp. AC	**−0.46** (2.30)	1.69 (2.46)	1.22 (2.62)	1.66 (2.57)	2.63 (2.31)	2.43 (2.40)	3.03 (2.55)	1.98 (2.20)
Top 2 comp. Rock	3.42 (2.80)	**−0.20** (3.00)	4.83 (3.16)	2.93 (3.05)	5.11* (2.82)	4.46 (2.92)	3.07 (3.04)	3.45 (2.71)
Top 2 comp. CHR	3.07 (3.34)	4.53 (3.59)	**−1.04** (3.90)	4.99 (3.67)	4.64 (3.38)	3.93 (3.52)	5.11 (3.70)	3.99 (3.22)
Top 2 comp. Urban/Alt.	0.20 (3.10)	0.94 (3.30)	−4.48 (3.59)	**−0.58** (3.29)	0.42 (3.11)	0.46 (3.23)	3.66 (3.39)	1.52 (2.97)
Top 2 comp. News/Talk	−0.23 (2.28)	0.35 (2.46)	−3.91 (2.63)	−2.64 (2.52)	**−2.02** (2.30)	−1.13 (2.39)	−1.65 (2.52)	0.28 (2.19)
Top 2 comp. Country	−1.72 (2.45)	0.10 (2.63)	0.79 (2.74)	−1.57 (2.72)	−0.55 (2.49)	**−5.42**** (2.57)	−1.51 (2.74)	−1.06 (2.35)
Top 2 comp. Spanish	4.03 (3.95)	1.70 (4.31)	3.47 (4.48)	−0.24 (4.29)	0.98 (3.88)	4.07 (4.14)	**−1.77** (3.85)	3.67 (3.72)
Top 2 comp. Other	5.00** (2.32)	3.64 (2.47)	5.99** (2.62)	4.38* (2.53)	4.85** (2.33)	4.93** (2.43)	1.79 (2.62)	**3.98*** (2.24)
Top 2 comp. Dark	−0.15 (0.43)	0.23 (0.48)	0.18 (0.48)	0.19 (0.48)	−0.08 (0.43)	−0.21 (0.43)	−0.24 (0.44)	−0.11 (0.41)

Standard errors (corrected for sequential estimation) in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Format-switching-strategy estimates: choice-specific coefficients on current portfolio of the player and top 2 competitors. The portfolio variables are measured as the number of owner stations in the format divided by the total number of stations in the market.

3 Robustness

In this section, I investigate the robustness of findings to various structural assumptions, using alternative estimators of the baseline specification. Tables 9 and 10 contain estimates for various alternative structural specifications and alternative estimators. Below I discuss rows of these tables.

3.1 Alternative specifications

First, I discuss alternative specifications I used to investigate robustness of the results to structural assumptions of the baseline model.

3.1.1 Move sequence (Tables 10 and 9, row 2)

The estimation depends on the assumed sequence of moves σ (see Section 3 in the paper). This assumption might be an important determinant of the results, so considering alternatives is of interest. For this reason, I recomputed the second-stage estimator considering a random sequence of moves. In particular, I assume players observe a new random ranking each period and move accordingly. Their strategies depend on the positions in the ranking because of fixed effects presented in Table 7 of the paper. I find such alteration of the game does impact estimates in a meaningful way. The within-format synergies are slightly smaller, amounting to 56%. The total impact of the Telecom Act is slightly bigger, amounting to \$1.243m.

3.1.2 Correlation structure of bundle acquisitions (Tables 10 and 9, row 3)

As mentioned in Section 3 of the paper, the timing prescribes the sequence of station-by-station acquisition and repositioning decisions, respectively, σ^A and σ^B. During the estimation, I assume players consider stations with a higher quality ξ first. The results might depend on this particular sequence, so I consider a specification in which the players consider stations in a random order. I find this specification produces results similar to the baseline; namely, the fixed cost savings from the Telecom Act amount to \$1,028m compared to \$1,193m in the baseline.

3.1.3 Cost of switching to/from DARK format (Tables 10 and 9, rows 4-7)

The baseline specification assumes that switching to/from the DARK format costs as much as switching to/from any other format. Because the DARK format is significantly different for other formats, one might worry this assumption might affect the second-stage estimates. The lack of data variation prohibits me from identifying DARK-related switching cost; thus I take a different approach. Namely, I estimate four additional specifications in which I set the following respectively: a 50% greater cost to switch from DARK, a 50% smaller cost to switch from DARK, a 50% greater cost to switch to DARK, and a 50% smaller cost to switch to DARK. I find that making these alternative assumptions essentially does not change the estimates of fixed cost and economies of scale. Also, for all but the "50% greater cost to switch from DARK" specification, the within-format synergy is close to the baseline. Specifically, "50% greater cost to switch from DARK" produces a 77% estimate of within-format synergy, which compares to 38% in the baseline. However, this specification also produces larger economies of scale and in the end provides the same estimate of the Telecom Act cost savings as the baseline. The overall cost savings predicted by these alternative specifications are bounded between $1,178m and $1,404m per-year.

3.1.4 Unobserved antitrust regulations (Tables 10 and 9, row 8)

The specification labeled "Antitrust cap at 40% market share" investigates how an additional antitrust cap could affect the results. The anecdotal evidence I gathered is that in the vast majority of cases, no antitrust rules beyond the ownership caps were in play on the local level. However, investigating how such a rule would affect the bottom line might still be useful because, an unaccounted antitrust rule could potentially explain the flat average cost curve beyond the second station. I consider a fairly strict rule by which the antitrust authority conducts a sophisticated static merger simulation. Namely, each time the merger is proposed, the agency recomputes the static equilibrium, and rejects the merger if the market share of the merged company exceeds 40%. Such specification indeed produces larger estimates yet also much lower estimates of the fixed cost. Also, because some mergers are rejected, the deviation rules used to construct the inequalities are weaker, resulting in a flatter objective function. In effect, the fixed cost for the "1M-2.5M" market category is not numerically identified and converges to a corner solution. Overall, the Telecom Act fixed-cost savings amount to $742m, which is smaller than the baseline but still economically significant.

In addition to investigating alternative specifications, I consider alternative BBL estimators of the baseline model. The results of these investigations are presented below.

3.2 Alternative BBL estimators

The last four rows of tables 9 and 10 investigate alternative estimators of the baseline specification. Respectively, I consider alternative inequalities and an alternative first stage.

3.2.1 Alternative inequalities (Tables 10 and 9, row 9-11)

I start by considering a removal $V > 0$ inequality, which essentially drops the assumption that radio owners can exit the market for free. I find this specification produces unreasonably high values for fixed cost, at the level of three times the revenue. Moreover, it generates an extreme level of within-format synergies, and produces an estimate on \$9b savings from the Telecom Act. Note that even though the estimates of the fixed-cost savings are unreasonably high, this exercise is still useful. If the true model contains a weaker form of the exit assumption, the truth should lie somewhere between \$1b and \$9b of cost savings, which strengthens my bottom line.

To investigate a robustness of my estimates to chosen deviations, I consider alternative suboptimal strategies. First, I consider a weaker deviation; that is, a merger deviation is applied only in a random half of the cases. This deviation produces a flatter objective function, especially along the cross section separating within-format synergies and economies of scale. This flatness is not surprising, because the separation of these two effects requires a diverse set of suboptimal mergers, spanning new formats and formats that are already owned. Applying weaker deviation shrinks this set. In effect, the estimate allocates all cost efficiencies into within-format synergy and produces a smaller but economically significant estimate of the Telecom Act savings of \$700m.

Second, I consider a stricter set of inequalities, which makes the first suboptimal merger 40% more probable. It makes the objective function less flat; however, it introduces extra noise. The average cost curve is identical to the original numbers, and within-format synergy is smaller and amounts to a 67% cost of an extra station compared to 38% in the baseline. All in all, the cost savings from the Telecom Act amount to \$710m.

3.2.2 Alternative first stage (Tables 10 and 9, row 12)

Another robustness check is considering richer first-stage parameterizations. Applying richer parameterizations is useful because in the perfect world, the first stage should be estimated nonparametrically. Instead, I use a flexible parametric form that captures most of the important variation in the data. The particular specification I use might not exhaust the data variation. To investigate that possibility, I consider richer first-stage specifications for acquisition and format-switching strategies, and reestimate the first and second stages of the model. Namely, I allow 30 extra parameters in each of the strategies. These parameters consist of (i) market category dummies, (ii) an interaction between category dummies and a format of the target station in case of acquisition, and (iii) an interaction between category dummies and the new format in case of format switching. I find that considering these richer specifications does not affect the estimates.

In sum, I find that my qualitative result, namely, that cost synergies outweigh the loss in consumer surplus caused by mergers after the Telecom Act, is robust to various perturbations of key structural assumptions and to using alternative estimators.

	Average fixed cost number of stations owned				Within-format synergy	Telecom Act cost savings
	2	4	6	8		
Main estimates	0.72 (0.21)	0.65 (0.25)	0.69 (0.22)	0.75 (0.19)	38% (29)	-\$1,193m
Alternative specification: Random sequence of moves	0.73	0.66	0.70	0.76	52%	-\$1,243m
Alternative specification: Random ordering of stations	0.69	0.61	0.65	0.73	32%	-\$1,028m
Alternative specification: 50% greater cost to switch from DARK	0.61	0.52	0.57	0.66	77%	-\$1,178m
Alternative specification: 50% smaller cost to switch from DARK	0.67	0.59	0.64	0.71	29%	-\$1,404m
Alternative specification: 50% greater cost to switch to DARK	0.69	0.62	0.66	0.73	35%	-\$1,270m
Alternative specification: 50% smaller cost to switch to DARK	0.69	0.62	0.66	0.73	35%	-\$1,270m
Alternative specification: Antitrust cap at 40% market share	0.64	0.55	0.60	0.68	74%	-\$742m
Alternative estimator: Drop $V > 0$ inequalities	0.51	0.39	0.46	0.57	3%	-\$8,875m
Alternative estimator: Interactions of market type with covariates in the first stage	0.65	0.57	0.61	0.70	32.09%	-\$1,001m
Alternative estimator: Weaker deviation	1.00	1.00	1.00	0.99	2%	-\$728m
Alternative estimator: Larger deviation	0.72	0.65	0.69	0.76	67%	-\$710m

Table 9: Robustness check: cost efficiencies.

	Fixed cost θ_m^{FIX}				θ^{ϕ}
	>2.5M	1M-2.5M	0.5M-1M	<0.5M	
Main estimates	10.44*** (2.25)	1.98 (1.21)	1.16** (0.46)	0.00 (0.02)	1.36*** (0.48)
Alternative specification: Random sequence of moves	11.09	2.51	1.10	0.04	1.23
Alternative specification: Random ordering of stations	8.70	1.59	1.04	0.00	0.73
Alternative specification: 50% greater cost to switch from DARK	10.66	2.02	1.21	0.00	1.37
Alternative specification: 50% smaller cost to switch from DARK	11.69	2.22	1.31	0.00	1.32
Alternative specification: 50% greater cost to switch to DARK	10.83	2.06	1.21	0.00	1.34
Alternative specification: 50% smaller cost to switch to DARK	10.83	2.06	1.21	0.00	1.34
Alternative specification: Antitrust cap at 40% market share	7.99	0.00	0.85	0.01	0.93
Alternative estimator: Drop $V > 0$ inequalities	63.99	16.12	4.74	0.00	1.84
Alternative estimator: Interactions of market type with covariates in the first stage	7.59	2.37	0.81	0.00	1.10
Alternative estimator: Weaker deviation	7.27	1.41	0.83	0.06	1.11
Alternative estimator: Larger deviation	7.23	0.74	0.82	0.05	1.54

Table 10: Robustness check: fixed cost.

References

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