

NBER WORKING PAPER SERIES

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IN RADIO BROADCASTING

Steven Berry  
Joel Waldfogel

Working Paper 5528

NATIONAL BUREAU OF ECONOMIC RESEARCH  
1050 Massachusetts Avenue  
Cambridge, MA 02138  
April 1996

We are grateful to Shelly Cagner of Arbitron for helping us get access to data and to James Duncan for helping us understand his data. We thank the Social Science Research Fund at Yale for financial support and seminar participants at Northwestern and Princeton for helpful comments. Andres Lederman and Jakub Rehor provided able research assistance. This paper is part of NBER's research programs in Law and Economics, and Industrial Organization. Any opinions expressed are those of the authors and not those of the National Bureau of Economic Research.

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ABSTRACT

In theory, free entry can lead to social inefficiency. When new products are substitutes for existing products, the business stolen from incumbents places a wedge between private and social benefits of entry. The business stealing effect can be offset if entry reduces prices or increases available product variety. Our study of the radio industry provides one of the first empirical attempts to quantify the inefficiency associated with free entry. Using data on advertising prices, number of stations and radio listening in 135 U.S. metropolitan markets, we estimate how listening and revenue vary with the number of stations. Using a free-entry assumption, we infer the distribution of station costs, which are fixed with respect to listening. We then use our estimates of revenue and fixed costs to calculate the welfare of market participants (excluding listeners) and the number of stations under free entry and social optimality. Relative to the social optimum, the welfare loss of free entry is 40 percent of industry revenue. However, we calculate that the free entry equilibrium would be optimal if the marginal value of programming to listeners were over three times the value of marginal listeners to advertisers, who pay 4.5 cents per hour.

Steven Berry  
Department of Economics  
Yale University  
New Haven, CT 06520  
and NBER

Joel Waldfogel  
Department of Economics  
Yale University  
New Haven, CT 06520  
and NBER

## I. Introduction

It is now well known, at least in theory, that free entry can lead to social inefficiency.<sup>1</sup> Excessive entry can result when two conditions hold: first, entrants' products are substitutes for existing firms' products, so that entry "steals business" from incumbents; and second, average costs are decreasing in output. An extreme example, with perfect substitutes, fixed prices, and exclusively fixed costs, illustrates this clearly. A second entrant garners half of the market and halves the incumbent's output. Consumers derive no additional benefit from the new entrant's product, but resource use on fixed costs are now doubled, reducing social surplus. The logic of free entry dictates that firms enter as long as the private benefit accruing to an entrant exceeds fixed costs. When new products are substitutes for existing products, the business stolen from incumbents places a wedge between private and social benefits of entry. In general the business stealing effect can be offset if entry reduces prices or increases available product variety, so that entry can be either excessive or insufficient.

Although these theoretical arguments have been advanced repeatedly in the past decades, we are aware of no empirical studies quantifying inefficiency associated with free entry. This may be because the data needed to document such a finding are hard to obtain. To calculate the optimal number of firms in an industry, one needs information on revenues and costs. In particular, one needs to know how revenue per firm changes with entry. Recent studies of entry (for example, Bresnahan and Reiss, 1990; Berry, 1992) are built

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<sup>1</sup>See Chamberlin (1933), Dixit and Stiglitz (1977), Mankiw and Whinston (1986), Spence (1976a,b), and Anderson, DePalma, and Nesterov (1995).

around a more easily observed datum, the number of firms in a market. Here we fill a gap in this literature with a study of entry into the U.S. commercial radio broadcasting industry. The idea that entry into radio markets may be inefficient goes back to Steiner (1954), who constructed examples with wasteful duplication. Two features of the radio industry suit it well for such a study. First, detailed data on firms' listening shares and advertising rates allow estimation of firms' revenue functions. Second, the radio industry is characterized by free entry (up to some technological limit) and high fixed costs.

Our model of the radio industry is simple: firm revenue equals a price (the annual advertising revenue per listener) times the number of listeners, while costs are fixed. The share of people listening to radio increases with available variety which, in turn, increases with the number of stations available in the market. Thus, cities with large population can support more stations than small cities. Availability of data on both listening and advertising prices allows us to estimate two functions associated with firm revenue, the listening share function and the inverse demand curve for advertising. The listening share function is derived from a nested logit model of consumers' listening decisions estimated from market level data, as suggested by Berry (1994). The inverse demand curve for advertising gives advertisers' marginal willingness to pay for listeners as a function of the listening share. These functions allow us to estimate how firm revenue varies with entry. In the same spirit as Bresnahan and Reiss (1990) and Berry (1992), we infer the distribution of fixed costs from entry decisions.<sup>2</sup> In contrast to earlier work, our fixed cost estimates employ an explicit revenue function that is identified without the entry model. The entry model is based on the

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<sup>2</sup>See also Dranove, Shanley, and Simon (1992).

equilibrium condition that we will observe  $N$  firms in a market if and only if  $N$  firms are profitable while  $N+1$  firms are not. Like earlier work we employ the simplifying assumption that firms are symmetric, so that post-entry profits depend only on the number of firms.<sup>3</sup>

Using the estimated revenue functions and fixed cost distributions, we can calculate the number of firms under free entry and monopoly. Given a notion of social welfare, we can also calculate the socially optimal number of firms. In most of this study we consider only the welfare of the paying customers, that is the advertisers. We defer until the end of the paper the issue of the externality created by the production of advertising, the value of programming to listeners. Because programming is an unpriced good, we have no data on its value, so we calculate the implied value of programming to listeners that would render observed entry optimal. We calculate social welfare under both free entry, monopoly, and optimality. The difference between welfare at the social optimum and welfare under free entry is a measure of the inefficiency of free entry into radio broadcasting.

The plan of the paper is as follows. Section II reviews the standard theory of entry into oligopolistic markets. Section III describes the data used in the study and documents some relationships in the data. Section IV adapts the standard theory to radio broadcasting and presents our econometric specification. Section V presents estimation results, as well as estimates of the social inefficiency of free entry into radio broadcasting. Section V also contains discussions of fit, estimates of the value of programming to listeners needed to

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<sup>3</sup>To relax this assumption we need to allow stations to choose their characteristics (e.g. format and quality) which significantly complicates the entry model.

render free entry optimal, and a description of directions for future research. A brief conclusion follows.

## II. Theory

We model radio broadcasting as a homogeneous goods industry, where the product is listeners who are "sold" to advertisers. In this section we review the standard theory of entry into such markets. (The empirical section below specifies particular functional forms that are appropriate for this industry and our data). The production process in broadcasting is unusual in that the primary inputs, listeners, are not purchased by the firm but rather make a free choice about listening to radio. Listeners' choices result in the share,  $s(N)$ , of the population listening to a given station as a function of the number of entering stations ( $N$ ). Total listening to radio is then  $Ns(N)$ , which we also term  $S(N)$ . The price of advertising,  $p$  (revenue per listener), is assumed to decline in the total listening share:

$$p(N) = p(Ns(N)).$$

Two assumptions are implicit in this formulation. First, our treatment of demand implicitly assumes a variant of the Cournot model: given the number of listeners "produced," price is determined by the market demand curve. Our approach deviates from the usual Cournot model in that output is determined by listener behavior rather than a traditional production function. Second, we model price as a function of listening share, rather than total listeners. Our specification is consistent with an explicit model of advertiser behavior in which the number of advertisers varies proportionately with market size  $M$ . We also assume that there is a fixed cost,  $F$ , of setting up a radio station and that the costs of a station do not vary with

the number of listeners.

Given our homogeneous goods treatment of advertising demand, the entry problem is exactly that of Mankiw and Whinston (1986), section 3. In a free entry equilibrium, firms enter until profits are driven to zero, with profits given by

$$\pi(N) = Mp(N)s(N) - F,$$

where  $M$  denotes market size. Formally, given the integer constraint on  $N$ , the number of firms under free entry,  $N^F$ , satisfies the condition:  $\pi(N^F) \geq 0$  and  $\pi(N^F + 1) < 0$ .

The total benefit to market participants is the total benefit to advertisers (which is split between radio-station revenue and advertisers' surplus) minus the costs of operating the stations. Initially, we restrict our examination of social benefit to those benefits captured by market participants, and ignore the important (unpriced) externality captured by listeners. Assuming that a social planner cannot set the price of advertising, but can only control entry, the planning problem is to choose  $N$  to maximize social welfare,

$$M \int_0^{Ns(N)} p(x) dx - NF$$

The first-order condition for this problem is

$$Mp(N)[s + N \frac{\partial s}{\partial N}] - F = 0, \text{ or}$$

$$\pi(N) + MNp(N) \frac{\partial s}{\partial N} = 0.$$

The second term in this expression is negative as long as per station listening share declines in  $N$ . If the free entry number of firms,  $N^F$ , sets profits exactly to zero, then marginal social

welfare is negative at  $N^*$ . Thus, we expect the free entry number of firms to exceed the social optimum.<sup>4</sup> The goal of our empirical work is to quantify the extent of this excess entry and its effect on welfare.

As an alternative entry model, we might consider the entry decisions of a monopolist who controls all radio entry. The objective function is then to maximize:

$$N\pi(N) = R(N) - NF.$$

Note that the monopolist internalizes the business-stealing effect. However, it is easy to see that the monopolist values increases in output less than the social welfare maximizing planner, who cares about the infra-marginal benefit to advertisers of the reduction in price caused by new entry. Thus, the monopolist will choose a smaller  $N$  than is socially optimal.

### III. Data

The data in this study are from a cross section of U.S. metropolitan radio markets. The endogenous variables are the number of firms located inside the metropolitan areas, the share of population listening to radio, and the price of advertising. Exogenous variables include demographic characteristics of the metropolitan areas, notably the level of population. In some specifications we also treat the number of firms broadcasting from outside the metropolitan area as exogenous.

#### 1. Sources

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<sup>4</sup>Given the integer constraint, Mankiw and Whinston note that the free entry number of firms must exceed the socially optimum number minus one.



Data for this study come from two sources, Arbitron (1993) and Duncan (1994). Arbitron provides data on the number of listeners to each commercial radio station in each major U.S. market in Spring 1993, as well as whether the station broadcasts from within a metropolitan area. The Arbitron data are generated from listening diaries submitted by compensated survey participants.<sup>5</sup> The Spring Arbitron survey includes data on every commercial radio station with positive reported listening in over 260 metropolitan statistical areas (MSAs). Duncan (1994) reports aggregate 1993 advertising revenue for the top stations in each of 135 MSAs.<sup>6</sup> We use this information to calculate annual advertising revenue per listener, which is our measure of advertising price,  $p$ . The city characteristics data, including total population and other demographics, are from Arbitron (1993), derived from U.S. Census figures.

The Arbitron listening figure we use is the average quarter hour rating (AQH). A station's AQH shows the number of persons listening to the station for at least five minutes during a quarter hour, averaged over quarter hours throughout the week (Monday-Sunday, 6:00 AM to midnight). At the city level we calculate the share of population listening to stations broadcasting from inside the metropolitan area  $S_1$ , the share listening to stations broadcasting from outside the metro area  $S_2$ , the number of commercial stations inside the metro  $N_1$ , and the

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<sup>5</sup>Arbitron receives listening diaries from roughly 1 in 500 persons in the markets (proportionately fewer in large markets, for example, 1 in 1800 in New York).

<sup>6</sup>Most major radio stations share their annual revenue figures with one of two accounting firms that serve the radio industry. Duncan (1994) reports the sum of the participating firms' revenue figures in each MSA and identifies which firms report. This allows us to calculate annual advertising revenue per listener in each MSA based on data for participating firms. Participating firms typically account for over three quarters of total listening.

number outside the metro but received inside the metro  $N_2$ . The data set used in the study includes information on 3269 stations in 135 markets (2519 inside and 777 outside). Because our model assumes post-entry symmetry of firms, the listening share of each inside firm is simply  $s_i = S_i/N_i$ .

Table 1 reports means, standard deviations, minima, and maxima of these variables, along with income and demographic characteristics of the MSAs, for the 135 metro areas included in the estimates. During an average 15-minute period, 14.4 percent of the population listens to at least five minutes of radio.<sup>7</sup> The vast majority of the listening (12.9 percentage points of the 14.4) is to stations broadcasting from inside the metro. The population of MSAs in the sample ranges from 133,000 to over 14 million. The number of inside-the-metro commercial radio stations varies from 6 to 46, with an average of 18.7. MSAs in the sample have an average annual household income of 36 thousand and an average fraction having some college of 47%. Finally, annual advertising revenue per listener averages \$277. Average annual revenue per market is \$37.8 million, which sums to \$5.1 billion for all 135 markets in the sample.

## 2. Relationships in the Data

The basic question we seek to answer with listening data is whether the share of population listening to a format grows as stations enter the market. Do stations simply split a pie (business stealing), or do they add listeners (market expansion)? If stations are identical,

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<sup>7</sup>Unlike Arbitron's reported total market AQH figures, which include both public and very small commercial stations, our total AQH listening includes only commercial stations attracting enough listeners to be listed independently in Arbitron.

then listeners will be indifferent between stations, and entry will not expand the market. Instead, a new entrant simply steals business from the incumbent(s). On the other hand, if stations are differentiated, then an entrant will draw listeners from both market expansion and business stealing.

How does the share of population listening to radio vary across cities with the number of stations available in those cities? Figure 1 shows that, while the listening share increases with the number of stations, it increases rather slowly. The flat relationship between listening and stations depicted in figure 1 offers suggestive evidence that the effect of a marginal entrant on listening is small, at least in markets with many incumbents. However, we cannot infer the causal link between the number of stations and the share of listeners from such a figure. The number of stations in a market is endogenously determined by the willingness of people in the market to listen to such programming. Hence, we need stronger techniques to allow us to infer the effect of entry on listening.

Figures 2 and 3 show the relationships among some other important variables relevant to our modelling exercise. Figure 2, which shows positive relationships between population and stations (both total and in-metro), demonstrates that markets with more people can support more stations. Figure 3 documents a negative relationship between the in-metro listening share and the advertising price. This is consistent with advertisers having a downward-sloping demand curve for listeners. The relationships in figures 1-3 help motivate our modelling strategy, but an explicit model is needed to guide our interpretation of the relationships among variables.

#### **IV. Econometric Specification**

To estimate the model, we specify a process that generates the data, including functional forms for the listening share function, the advertising demand function, and the distribution of fixed costs. Our discussion will specify an error structure for each equation as well as a set of exogenous data.

### 1. The Listening Share Function

We use a simple discrete choice formulation for listeners' choices. Each person in the market chooses among a set of choices that includes each station in the market and also includes the choice of not listening. Each additional station brings some unique benefit to consumers, but may also steal listening from existing stations. We use a nested logit utility function to parameterize the degree to which stations offer unique, as opposed to redundant, programming.

The utility of potential listener  $i$  for station  $j$  is then given by function:<sup>8</sup>

$$u_{ij} = \delta_j + \nu_i(\sigma) + (1-\sigma)\varepsilon_{ij}$$

where  $\delta_j$  is the mean utility of listening to station  $j$  and  $\varepsilon_{ij}$ , an i.i.d. extreme value deviate, is the idiosyncratic benefit of this station for this person. As the parameter  $\sigma$  goes to one, stations become identical and the only random term in the utility function is  $\nu_i$ , which is constant across all stations. The common term  $\nu_i$  has a distribution, derived in Cardell (1992), that goes to zero as  $\sigma$  goes to zero. Therefore, when  $\sigma$  is zero, we return to the logit model and stations give completely idiosyncratic benefits. To complete the specification, the utility of not listening is

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<sup>8</sup>To the best of our knowledge, the nested logit choice probability was introduced by Ben-Akiva (1973) and shown to be consistent with a discrete choice model by McFadden (1978). The explicit form for the nested logit utility function used here is taken from Cardell (1992).

random and given by the extreme value deviate,  $\varepsilon_{it}$ .

In the nested logit specification, the term  $\delta_j$  then captures the average benefit of listening, as opposed to not listening, while  $\sigma$  parameterizes the business-stealing effect. As  $\sigma$  goes to one, the business-stealing effect is complete and an additional station does not increase total listening. For smaller values of  $\sigma$ , total listenership increases in the number of stations, with a maximum rate of increase when  $\sigma$  is zero. This can be seen from the nested logit choice probabilities. For station  $j$ , the share of the market listening is

$$s_j(\delta, \sigma) = \frac{e^{\delta_j/\sigma}}{D} \frac{D^{1-\sigma}}{(1+D^{1-\sigma})},$$

where

$$D = \sum_j e^{\delta_j/\sigma}$$

The first term in the expression for  $s_j(\delta, \sigma)$  is the share of station  $j$  as a fraction of total radio listening, while the second expression is the total radio listening share.

In order to maintain the tractability of the entry model, we assume that all stations in a given market have identical mean utility levels and therefore identical post-entry market shares. Given identical mean utility levels, the listening share of a station is just a function of  $\sigma$ ,  $\delta$ , and the number of entering stations,  $N$ :

$$s_j(N, \delta, \sigma) = \frac{1}{N} \frac{N^{1-\sigma}}{V_0 + N^{1-\sigma}}, \text{ where}$$

$$V_0 = e^{-\frac{1-\sigma}{\sigma} \delta}.$$

To estimate the model, we parameterize the mean utility of a station in market  $k$  as

$$\delta_k = x_k \beta + \xi_k$$

The term  $x_k$  is a vector of observed market characteristics,  $\beta$  is a vector to be estimated and  $\xi_k$  is an unobservable assumed to be mean independent of the exogenous data. To estimate the parameters,  $\beta$  and  $\sigma$ , of listener utility, we follow the method in Berry (1994) exactly. Given the observed per station market share,  $s_k(N)$ , we can invert the nested logit market share function to solve for  $\delta_k$  as a function of the parameter  $\sigma$ . The unobservable  $\xi_k$  is then defined as

$$\xi_k(\delta, \sigma) = \delta_k(\sigma, s_k) - x_k \beta.$$

Given a vector of exogenous data,  $z_k$ , a method of moments estimator can then be formed from the moment conditions:

$$E[\xi_k(\delta, \sigma) | z_k] = 0.$$

In our case, the exogenous data consists of the  $x$  vector, population, and the number of stations broadcasting from outside the metro. Berry (1994, equation 24) shows that  $\delta$  is linear in  $\sigma$ , so two-stage least squares, for example, can be used as the method of moments estimator.

## 2. The Demand for Listeners

Given a number of listeners, a station then produces revenue by "selling" these listeners to advertisers. We assume that there is a fixed number of advertising minutes sold per hour and that the price of a single advertisement sold by a station is proportional to the number of listeners to that station. (There are interesting questions about the endogeneity of the number of advertisements per hour and about different advertising rates for different demographic groups that, for lack of data, we will not address here). Consequently, total revenue of a station is the market ad price per listener times the average number of listeners.

We allow advertisers' marginal willingness-to-pay for listeners to decline in the share of

population listening to radio. In the empirical work, we adopt a simple constant elasticity specification for the inverse advertising demand curve:

where  $\eta$  is the inverse elasticity of demand,  $\alpha$  is a parameter that shifts demand, and  $S(N)$  is the share of population listening to radio.

$$p = \alpha(S(N))^{-\eta},$$

We assume that the demand parameter  $\alpha$  is a function of observed demand shifters  $x_k$  and an unobserved error  $\omega_k$ . Assuming that  $\ln(\alpha) = x_k + \omega_k$ , the inverse demand curve for advertising is defined by:

$$\ln(p_k) = x_k\gamma - \eta\ln(S_k) + \omega_k,$$

where  $S_k = N_k s_k(N_k)$  is the observed total listening share of radio in market  $k$ , and  $\gamma$  and  $\eta$  are parameters to be estimated. The term  $\omega_k$  is an unobservable shock to advertising prices that is assumed to be mean independent of the exogenous data:

$$E[\omega_k(\gamma, \eta) | z_k] = 0.$$

The endogenous data are  $p$  and  $S_k$ , while the exogenous data  $z_k$  include instruments for the endogenous variable  $S_k$ . Again, given the linearity of our functional form this equation may be estimated via instrumental variables methods, such as two-stage least squares. The instruments are the same as in the estimation of listening demand.

### 3. The Distribution of Fixed Costs

We assume that fixed costs are equal for every station in the market and are distributed log-normally across markets. In particular, we assume that fixed costs are:

$$\ln(F_k) = x_k \mu + \lambda v_k$$

where  $v_k$  is distributed standard normal, while  $\mu$  and  $\lambda$  are parameters to be estimated. As in Bresnahan and Reiss (1990), the assumption that fixed costs are equal for all firms leads naturally to the “ordered probit” likelihood function. However, unlike Bresnahan and Reiss (1990) we have data on post-entry outcomes and need only estimate the parameters of fixed costs from the ordered probit (as opposed to estimating all the parameters of the profit function from the ordered probit).

A number of firms equal to  $N_k$  is observed in equilibrium if and only if fixed costs are such that  $N_k$  stations make a profit but  $N_k+1$  stations would not. That is,  $F_k$  must fall between the value of variable profits given  $N_k$  stations,  $v_k(N) = Mp(N)s(N)$ , and the value of variable profits given  $N_k+1$  stations. The term  $v_k(N_k)$  is just the product of observed population, advertising price and per station market share. The term  $v_k(N_k+1)$  is easy to calculate given our functional form assumptions.

The likelihood function is then

$$L(\theta) = \Phi\left(\frac{\ln(M_k P_k(N_k) s_k(N_k)) - x_k \mu}{\lambda}\right) - \Phi\left(\frac{\ln(M_k P_k(N_k+1) s_k(N_k+1)) - x_k \mu}{\lambda}\right)$$

Where  $\Phi$  is the standard normal cdf. Our estimates of the parameters of fixed cost maximize the log-likelihood function of the data, conditional on our earlier estimates of the parameters of variable profit. The estimation error in the listening and advertising price parameters will cause the usual maximum likelihood standard errors to be incorrect. For this reason, we also estimate all the parameters of the problem jointly.



#### 4. Joint Estimation

Each of the estimation problems above can be thought of as method of moments. The moments associated with the listening and ad price equations are formed from the interactions of the equation "errors" and the exogenous data. The MLE first-order conditions (with respect to the parameters of the distribution of fixed costs) are also properly thought of as moment conditions. To estimate the parameters of all three equations jointly, we simply stack the three sets of moment conditions and estimate by generalized method of moments. The vector of sample moment conditions, as a function of all the parameters is:

$$g(\theta) = \sum_k \begin{bmatrix} \xi_k(\beta, \sigma) z_k \\ \omega_k(\gamma, \eta) z_k \\ \frac{\partial \ln(L_k(\theta))}{\partial (\mu, \lambda)} \end{bmatrix}$$

As we will see in the empirical section, equation-by-equation and joint estimation give nearly identical results. However, the standard errors of the joint estimates are correct.

### **V. Results**

#### 1. Parameter Estimates

Table 2 reports estimated parameters. Columns 1 and 2 report listening share parameters

from single-equation specifications of the listening share function. In addition to OLS estimates (column 1), we also report two stage least squares (TSLS) results using metro population and stations outside the metro ( $N_2$ ) as instruments for  $N_1$ , as well (column 2).<sup>9</sup> All of the parameter estimates - including the estimates of the important parameter  $\sigma$  - are quite similar across specifications. The per-station listening share is higher in each of the included regions (northeast, north central, and south) than in the excluded western region. There is weak evidence that per-station listening is higher in cities with higher per-capita income and lower in cities with a large fraction of college-educated residents. Estimates of  $\sigma$  are also robust to exclusion of market characteristics variables (region dummies, income, and percent college educated). The estimates of  $\sigma$  are all roughly 0.8, indicating that commercial stations are strongly substitutable for one another. To illustrate the meaning of our parameter estimate, consider a hypothetical market with one station attracting 10 percent of the population as listeners. If  $\sigma$  is 1 the second station has no effect on overall listening. If  $\sigma$  is 0 (the logit case), a second station increases total listening by over 80 percent (to 18.2 percent of the population). With  $\sigma = 0.8$ , the second station increases total listening only slightly, from 10 to 11.3 percent. The similarity of OLS and TSLS estimates of  $\sigma$  indicates that  $N_1$  is determined largely by our instruments (population and outside the metro competition) and not by city-specific variation in tastes for radio that we do not observe.

Columns 3 and 4 of table 2 report results of single-equation estimation of advertising demand. The price of advertising per listener is highest in the north central region, followed by the south, the northeast, and the west. The advertising price is higher in high-income cities

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<sup>9</sup>We obtain very similar results using only population as an instrument.

and in highly educated cities. In both specifications the demand for advertising is elastic, and the elasticity is roughly 1.72 (1/0.582). Once again, instrumenting has little effect on the results.

Column 5 reports estimates of the fixed cost parameters from the entry model estimated via the ordered probit holding the listening and advertising coefficients fixed at their estimated (TSLS) values. The ordered probit coefficients describe the mean of the distribution of log fixed costs. The mean of station fixed costs has the same ordinal pattern as the advertising price. It is highest in the north central region, followed by the south and northeast, then the west. Fixed costs are higher in high-income and high-education cities. We include population in the specification for fixed costs to reflect the possibility that inputs may be more costly in large cities, and fixed costs rise in population.<sup>10</sup> The parameter  $\lambda$ , the estimated standard error of log fixed costs, is 0.23. This turns out to imply that the variance in fixed costs conditional on city characteristics is about one quarter of mean fixed costs.

The last column of table 2 reports results from joint GMM estimation of the entire model. These results are similar to the single equation results, but the standard errors of the fixed cost coefficients are corrected for the presence of other estimated coefficients. We concentrate on these results below.

## 2. Fit

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<sup>10</sup>Station fixed costs may also rise in population because of license rents. We explore this possibility below by re-estimating the model excluding the largest 25 markets. According to industry analyst James Duncan, license scarcity would be likely to arise only in those markets.

To gauge how well our model fits the data, we compare the model's implied number of stations inside each market with the actual number. We calculate the model's implied  $N_i$  by taking a large number of draws from the fixed cost distribution for each market. For each draw we solve for the highest integer number of stations yielding positive profit. The model will predict the observed number of stations (as a free entry equilibrium) only if fixed costs are drawn from the region of the fixed cost distribution consistent with observed  $N_i$ . We repeat this exercise 200 times. The correlation of model and actual  $N_i$  is 0.782, implying an  $R^2$  of 0.612. By contrast, OLS regression (which by design maximizes  $R^2$ ) of  $N_i$  on variables used in the study gives an  $R^2$  of 0.730. The OLS regression parameters have no direct economic interpretation and cannot be used to calculate social welfare.

### 3. Policy Simulations

Table 3 reports simulated values of the number of in-metro stations, costs, revenue, welfare, listening, and the advertising price for our sample. For all simulations, we draw from the part of the distribution of fixed costs consistent with the observed number of stations (recall that  $N$  stations in a market implies specific bounds on fixed costs). This ensures that the model's free entry number of inside stations equals the actual number in every simulation. We choose this approach because our concern is not with fit, but rather with the contrast among free entry, monopoly, and social optimality.

Table 3 clearly indicates that free entry into radio is excessive. While there are 2519 commercial stations in the 135 markets under free entry, the socially optimal number is 649 (with a standard error of 41.7). Compared with the current average of 18.7 inside stations per

market, the social optimum has 4.8 (0.31) inside stations per market. This is a reduction of 74.2 percent in the number of stations. Ignoring the value of programming to listeners - as commercial radio broadcasters naturally do - social welfare with the current (free entry) configuration of stations is \$5.82 billion per year (\$3.51 billion). With the optimal configuration of stations - again, ignoring listener welfare - social welfare is \$8.15 billion per year (\$3.51 billion), indicating that the deadweight loss of free entry into radio broadcasting in these markets is \$2.33 billion per year (\$224 million). This is over 40 percent of current (free entry) revenue.

It may seem strange to evaluate the social welfare of entry into radio broadcasting ignoring the benefit of programming to listeners. Recall, however, that the benefit that listeners receive is an external by-product of the revenue-generating activities of commercial broadcasting. Ours is the correct calculation for evaluating the efficiency with which firms provide advertising. There is a separate question of whether broadcast regulators are justified in allowing inefficient production of advertising because of the external benefit provided to listeners. We examine this question below, at section V.4.

The main source of welfare improvement from moving to the social optimum is the reduction in station operating costs, from \$5.01 billion (\$3.1 million) per year under free entry to \$1.15 billion (\$84.8 million) in the social optimum. The direct benefit of this \$3.86 billion annual operating cost reduction is considerably offset, however, by the increase in prices paid by advertisers, from \$276.6 to \$327.9 (\$9.99) per listener annually. Regulators could target the number of firms at the social optimum by two means. First, regulators could directly limit entry. Second, regulators could levy a tax on entry. Stations facing an entry tax equal to per-station profit under the social optimum (averaging \$5 million per station annually across

markets) would freely enter up to the optimal number of stations. Such a tax would collect \$3.2 billion in annual revenue.

Table 3 also shows the consequences of monopoly. Interestingly, monopoly would generate outcomes closer to the social optimum than does free entry. A monopolist (in each market) would operate fewer stations than is socially optimal (331 - with a standard error of 52.7 - as opposed to 649 - with a standard error of 41.7). Social welfare and revenue under monopoly are rather close to those in the social optimum. Welfare under monopoly is only 2.9 percent below the welfare maximum.

Table 4 reports simulation results for markets at the 20<sup>th</sup>, 40<sup>th</sup>, 60<sup>th</sup>, and 80<sup>th</sup> population percentiles. The table illustrates that the optimal number of inside stations increases little with population, while the free entry number of inside stations is nearly proportional to population. Consequently, the deadweight loss is both absolutely and proportionally larger in more populous markets.

#### 4. The Value of Programming to Listeners Implied by Free Entry

Up to this point we have ignored the external benefit of programming to radio listeners. The social optimum calculated above ignores listeners' valuation of radio programming. Here we ask: what listener valuation of an additional station renders free entry optimal? To answer this question we augment the welfare maximand of section II to include a component reflecting listeners' valuation of radio programming. We denote by  $L(N)$  the per capita benefit to listeners as a function of the number of stations, giving total welfare of:

We solve the associated first order condition, evaluated at the free entry  $N$ , for the value of the

$$M \int_0^{N_0(N)} p(x) dx - NF + ML(N) = W(N) + ML(N)$$

marginal station to listeners that implicitly renders free entry optimal:<sup>11</sup>

$$M \frac{\partial L}{\partial N} = - \frac{\partial W}{\partial N}$$

We can calculate the implied value of a marginal station in each market required to render free entry optimal. While we have little intuition about the interpretation of this quantity, we would like to compare the marginal value that listeners must place on entry with the value placed by the market.

Note that advertisers value increases in listening share,  $S$ . Listening share is a monotonic function of  $N$ , so we can also think of the value to listeners as a function of  $S$ ,  $L(N) = L(S(N))$ .

The marginal value to listeners of an increase in  $S$  is then

$$\frac{dL}{dS} = \frac{\partial L / \partial S}{\partial S / \partial N}$$

This number is easy to calculate and we find an average value for  $dL/dS$  of \$921.9 (\$154.2) per year of listening. In our data, a year of listening is eighteen hours per day for each day of the year, so \$922 per listener-year is about 15 cents per hour of listening. Because marginal entry is more wasteful in larger cities, the implied value of programming to listeners that renders free entry optimal grows with population (table 4 also illustrates this).

We can compare our implied value of increases in listening to the average observed

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<sup>11</sup>Waldfogel (1993) performs a similar exercise, inferring welfare weights underlying policy, in the context of criminal sentencing.

advertising price of \$277 per listener-year or about 4.5 cents per listener hour. Thus, to justify free entry, the external benefit of programming to listeners must be over three times the market value.

Note that the external benefit of listening share has two components. First, an increase in  $N$  attracts new listeners to radio. Second, the new station allows existing listeners to switch its possibly higher valued programming. Our implied value of  $dL/dN$ , and thus our value of  $dL/dS$ , includes both of these benefits. We have no direct evidence on the value that listeners in our sample attach to radio programming, so we leave it to other analysts to determine whether the actual value of programming to listeners renders free entry optimal in this context.<sup>12</sup>

## 5. Robustness and Future Directions

Our results may be sensitive to assumptions implicit in our framework and sample. First, our estimates of fixed costs may be affected by government restrictions on broadcasting that create license rents in large markets. The positive relationship between population and fixed costs might reflect this rather than other input prices that are higher in large cities. To test this we reestimated the model excluding the top 25 markets, and we obtain very similar results. The ratio of welfare loss to revenue was actually somewhat higher than our estimate using the full sample.

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<sup>12</sup>We have some indirect evidence on (minimum) valuations of radio programming from European license fees. As of 1988, only Belgium and Switzerland offered separate radio licenses but did not offer combined radio and television licenses. The license fees for Belgian and Swiss radio use were \$23.2 and \$59.4 per household per year, respectively, or \$8.5 and \$22.8 per capita annually in the two countries. Almost half of Belgian and Swiss households purchased radio licenses in 1987 (see European Broadcasting Union Review 1988).



Another possible problem with our approach is our treatment of stations located outside the metropolitan areas. Our model - and our simulation - treats the number of outside stations ( $N_2$ ) as fixed even as we optimally reduce  $N_1$ . Many stations that are outside of one market are inside of some other market. Thus  $N_2$  should probably decrease in the social optimum as other markets move to the optimal number of inside stations. We therefore redid our policy simulations using an *ad hoc* rule that reduced  $N_2$  proportional to our reductions in  $N_1$ . These simulations result in a larger deadweight loss from free entry. This is because advertisers actually value the listening stolen from outside-the-metro stations. With fewer outside stations, in-metro entry is more wasteful because business is stolen, to a greater extent, from other inside stations.

We are also concerned about the possible endogeneity of outside-the-metro entry. We could test whether our treatment of  $N_2$  as exogenous affects our results by reestimating the model including only "isolated" markets (with relatively few outside stations). As a rough approximation, we remove from the sample the 28 cities in the densely populated Northeast. These cities have an average ratio of outside-the-metro listening to inside-the-metro listening of 22 percent, while the remaining cities' ratio is less than 13 percent. The results are very similar. The estimate of  $\sigma$  remains about 0.8, the estimate of  $\eta$  falls a bit to about 0.3 (indicating more elastic advertising demand), and the welfare loss from free entry is about 45 percent of revenue.

Some of our simplifying assumptions are difficult to examine because relaxing them would substantially complicate our modelling. We assume that radio stations are symmetric within each market. This allows us to model entry as a one-dimensional decision: how many

firms. An important direction for future research is to allow for multiple types of stations, corresponding not only to different programming formats but also different levels of quality (e.g. wattage or on-air talent). Empirical work on entry to date has modelled heterogeneity in fixed costs (Berry, 1992) but not in variable profits. Such an effort would require substantially new methods. A similarly difficult but interesting extension would be to allow a single firm to own multiple stations.

## **VI. Conclusion**

In this study we have filled a gap in the empirical literature on the efficiency of free entry. Because we have data on firms' revenue we are able to estimate how revenue varies with entry. Consequently, our entry model generates direct estimates of the distribution of fixed costs. Given an explicit measure of welfare we determine the optimal number of stations. We then compare the number of stations and social welfare under free entry and optimality. Ignoring the value of programming to listeners we find that free entry into U.S. radio broadcasting causes a welfare loss of over 40 percent the size of current industry revenue. We can rationalize the number of stations under free entry as optimal if the value of programming about 15 cents per hour of listening.

The cost structure of radio broadcasting is an extreme case, with large fixed costs and zero marginal costs. This is the sort of situation in which free entry is most likely to be inefficient. Yet, we suggest that radio broadcasting is not unique. Many activities related to the production and distribution of information have similar characteristics, including the

computer software industry, television broadcasting, and print media. R&D-intensive industries also share this characteristic. Further study is needed to quantify the degree of inefficiency in such contexts.

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Figure 1  
Stations and Listening by Market

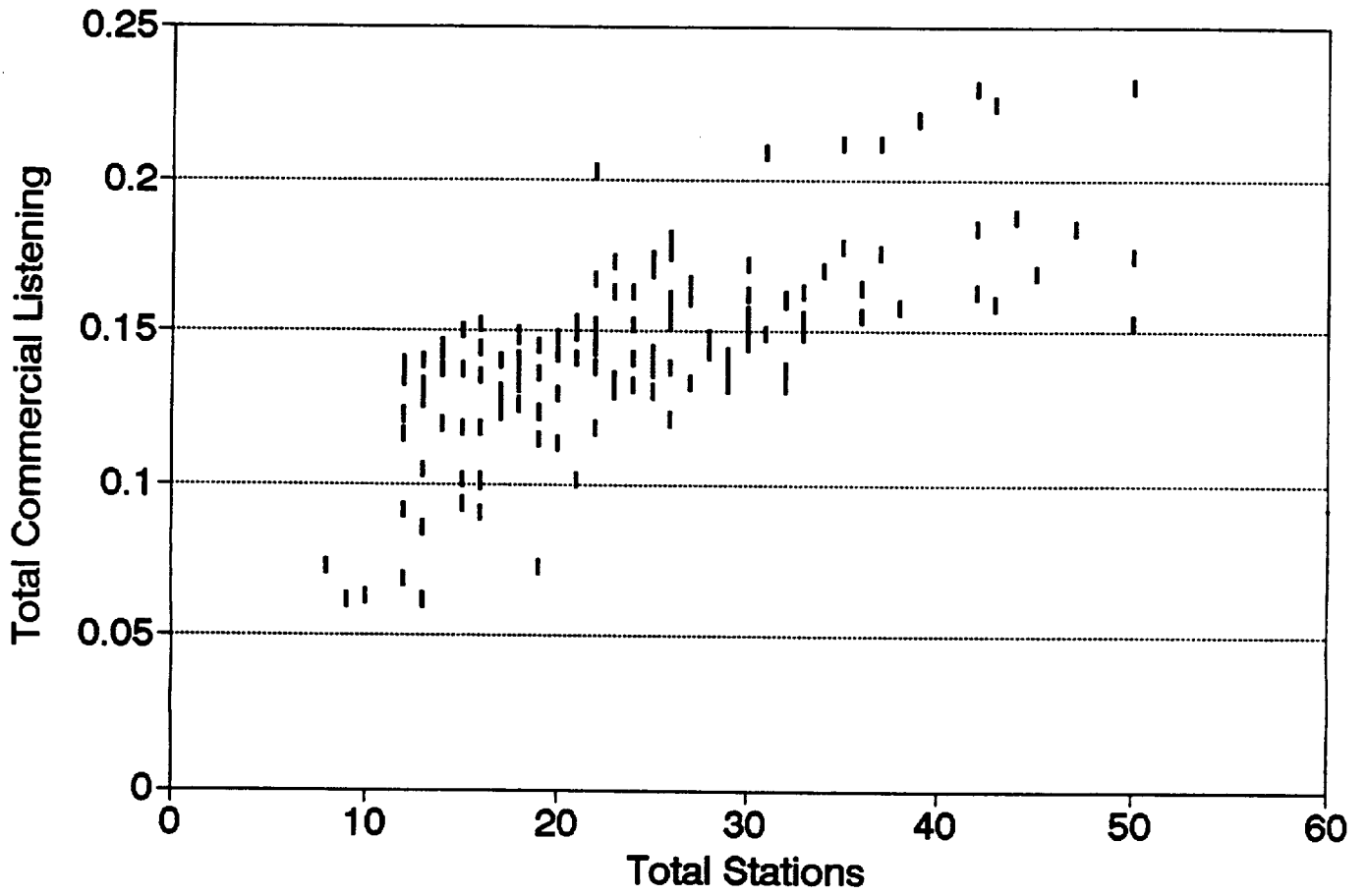


Figure 2  
Population and Stations by Market

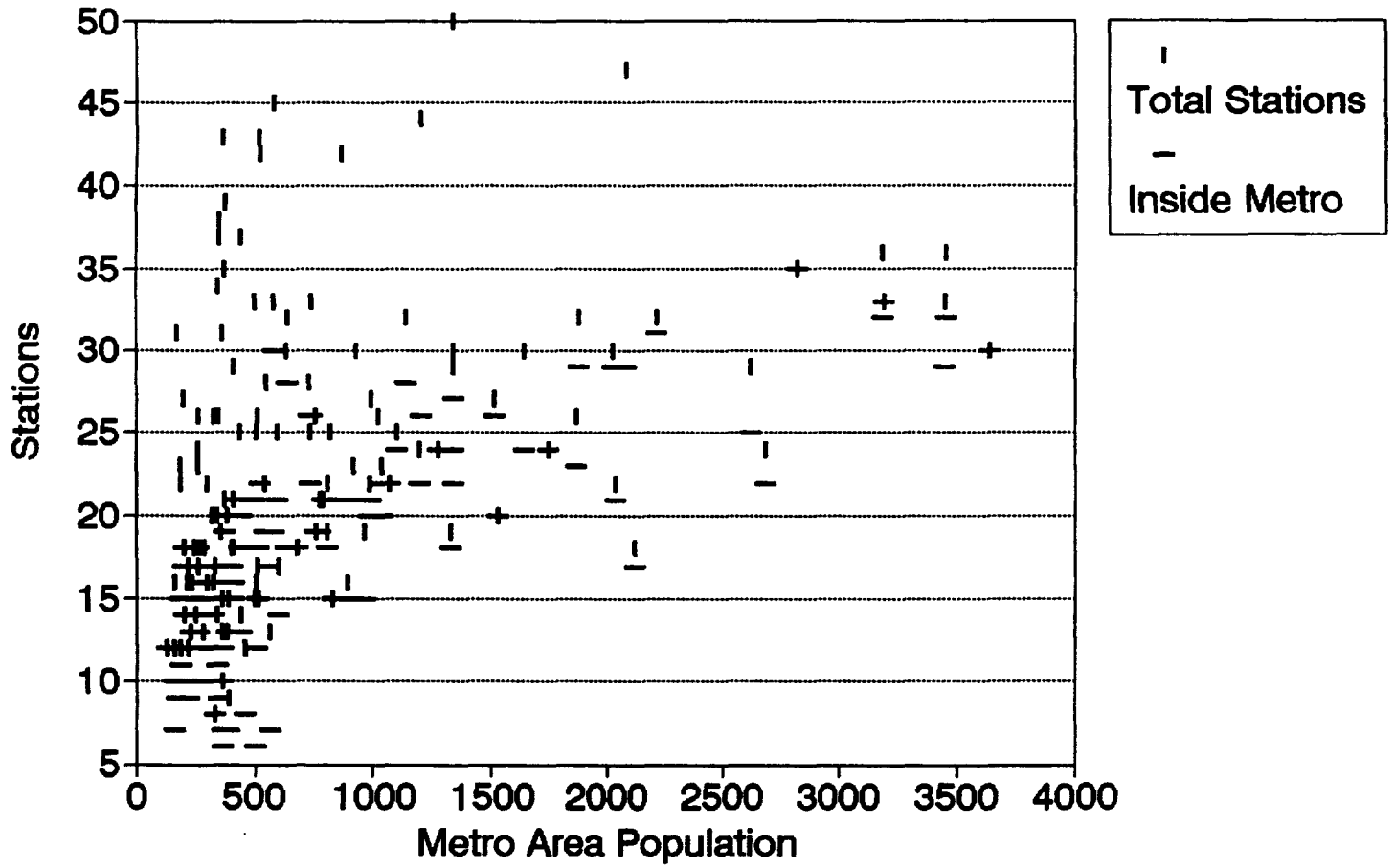
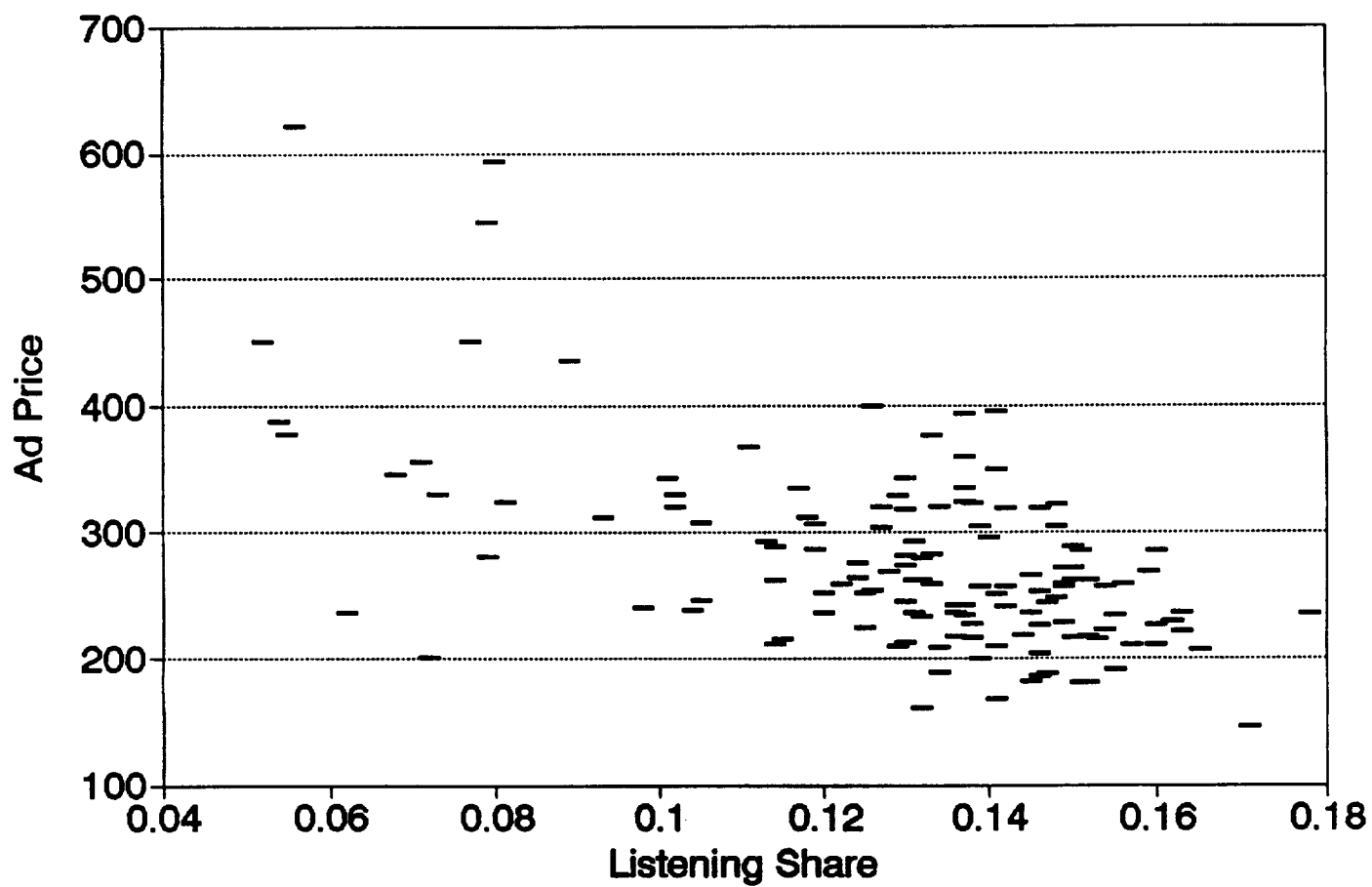


Figure 3  
In-Metro Listening Share and Ad Price





**TABLE 1: Description of City-Level Data**

Variable	Units	Mean	Std Dev	Min	Max
Share 1 (in metro)	proportion	0.129	0.129	0.052	0.178
Share 2 (out metro)	proportion	0.015	0.015	0.000	0.111
$N_1$ (in metro)	integer	18.659	18.659	6.000	46.000
$N_2$ (out metro)	integer	5.756	5.756	0.000	28.000
Population	millions	1.070	1.070	0.133	14.034
Adv Price (rev/listener)	\$100s	2.766	2.766	1.466	6.213
Income	\$1,000	35.553	5.384	21.860	51.936
College*	%	46.96	7.76	28.30	65.10

\* To scale coefficients, the income and college variables are divided by 10 in the empirical work.

**TABLE 1: Description of City-Level Data**

Variable	Units	Mean	Std Dev	Min	Max
Share in metro	%	12.932	2.633	5.172	17.841
Share out metro	%	1.543	2.513	0.000	11.142
$N_1$ (in metro)	integer	18.659	7.625	6.000	46.000
$N_2$ (out metro)	integer	5.756	7.105	0.000	28.000
Population	millions	1.070	1.704	0.133	14.034
Adv Price	\$100	2.766	7.595	1.466	6.213
Income	\$1,000	35.553	0.538	21.860	51.936
College*	%	46.969	0.776	28.300	65.100

\* To scale coefficients, the income and college variables are divided by 10 in the empirical work. Ad Price is per AQH listener-year.

**TABLE 2: Results from the Structural Model**

Parm	Share OLS	Share TSLs	Ad OLS	Ad TSLs	ENTRY	FULL
CONST	-2.240 ( 0.106 )	-2.338 ( 0.141 )	-- --	-- --	-- --	-2.326 ( 0.080 )
NEAST	0.070 ( 0.032 )	0.081 ( 0.034 )	-- --	-- --	-- --	0.067 ( 0.023 )
NCEN	0.061 ( 0.029 )	0.075 ( 0.032 )	-- --	-- --	-- --	0.075 ( 0.023 )
SOUTH	0.035 ( 0.026 )	0.042 ( 0.027 )	-- --	-- --	-- --	0.038 ( 0.023 )
INCOME	0.024 ( 0.023 )	0.014 ( 0.025 )	-- --	-- --	-- --	0.013 ( 0.020 )
COLLEGE	-0.029 ( 0.014 )	-0.026 ( 0.015 )	-- --	-- --	-- --	-0.029 ( 0.012 )
$\sigma$	0.843 ( 0.029 )	0.805 ( 0.046 )	-- --	-- --	-- --	0.802 ( 0.029 )
CONST	-- --	-- --	3.671 ( 0.203 )	3.735 ( 0.225 )	-- --	3.755 ( 0.257 )
NEAST	-- --	-- --	0.043 ( 0.063 )	0.044 ( 0.063 )	-- --	0.047 ( 0.076 )
NCEN	-- --	-- --	0.186 ( 0.054 )	0.186 ( 0.054 )	-- --	0.184 ( 0.060 )
SOUTH	-- --	-- --	0.109 ( 0.051 )	0.107 ( 0.051 )	-- --	0.102 ( 0.048 )
INCOME	-- --	-- --	0.053 ( 0.043 )	0.056 ( 0.043 )	-- --	0.069 ( 0.047 )
COLLEGE	-- --	-- --	0.094 ( 0.029 )	0.093 ( 0.029 )	-- --	0.087 ( 0.031 )
$\eta$	-- --	-- --	0.576 ( 0.066 )	0.546 ( 0.081 )	-- --	0.528 ( 0.115 )
CONST	-- --	-- --	-- --	-- --	-0.847 ( 0.201 )	-0.821 ( 0.018 )
NEAST	-- --	-- --	-- --	-- --	0.250 ( 0.067 )	0.251 ( 0.010 )
NCEN	-- --	-- --	-- --	-- --	0.409 ( 0.069 )	0.419 ( 0.031 )
SOUTH	-- --	-- --	-- --	-- --	0.274 ( 0.065 )	0.272 ( 0.023 )
INCOME	-- --	-- --	-- --	-- --	0.197 ( 0.050 )	0.190 ( 0.006 )
COLLEGE	-- --	-- --	-- --	-- --	0.081 ( 0.037 )	0.081 ( 0.003 )
Popl	-- --	-- --	-- --	-- --	0.631 ( 0.021 )	0.652 ( 0.032 )
$\lambda$	-- --	-- --	-- --	-- --	0.225 ( 0.015 )	0.226 ( 0.019 )
$R^2$	0.90	0.90	0.47	0.47		

**TABLE 3: Comparison of Free Entry, Optimality, and Monopoly**

	Free Entry	Optimal	Monopoly
In-Metro Entry	2519	649 (41)	331 (52)
Agg. Costs (\$m)	5013 (3)	1150 (84)	590 (98)
Agg. Revenue (\$m)	5106	4385 (189)	4011 (169)
Welfare (\$m)	5816 (3513)	8149 (3506)	7916 (3333)
Ad Price	276	327 (10)	381 (51)
Listening Share (%)	12.93	9.35 (0.19)	7.53 (0.48)

Note: Standard errors are in parentheses. The free entry numbers without standard errors are calculated directly from data. As noted in the text, the difference between free entry and optimal welfare has a standard error of 224.

**TABLE 4: Simulation Results for Selected Markets**

City	Modesto	Wilmington	Greensboro	Washington
<b>Description of City</b>				
Population (mil.)	0.3	0.5	0.9	3.5
Population percentile	20	40	60	80
Outside Stations	12	25	6	4
<b># of In-Metro Stations</b>				
Free Entry	16	6	21	29
Optimal	7 (0.3)	4 (0.5)	6 (0.4)	7 (0.5)
<b>% In-Metro Listening</b>				
Free Entry	10.1	5.4	11.5	14.8
Optimal	7.2 (0.2)	4 (0.4)	8 (0.2)	10.9 (0.3)
<b>Revenue (\$mil.)</b>				
Free Entry	11.3	10.5	22.8	164.4
Optimal	9.6 (0.5)	9 (0.6)	19.3 (0.9)	142.4 (6.2)
<b>Costs (\$mil.)</b>				
Free Entry	11 (0.1)	9.9 (0.1)	22.3 (0.1)	161.9 (0.1)
Optimal	4.8 (0.2)	6.6 (0.8)	6.4 (0.4)	39.1 (3)
<b>Welfare (\$mil.)</b>				
Free Entry	13 (7.8)	12.3 (7.3)	25.9 (15.7)	186.8 (113.1)
Optimal	15.6 (7.7)	12.6 (7.2)	34.5 (15.6)	262.8 (112.8)
<b>Ad Price (\$/list./yr.)</b>				
Free Entry	342.7	387.8	214.8	321.9
Optimal	411.4 (14.)	456.6 (13.8)	259 (8.6)	378.2 (12.8)
<b>Implied \$ Value per List-Yr</b>				
	613.3 53.1	118.2 5.8	698.6 96.9	1368.5 233.6

Note: Standard errors are in parentheses. The free entry numbers without standard errors are calculated directly from data.