# Optimal Product Variety in Radio Markets*

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**Abstract**

A vast theoretical literature shows that inefficient market structures may arise in free entry equilibria. The inefficiency may manifest itself in the number, variety, or quality of offered products. Previous empirical work demonstrated that excessive entry may obtain in local Radio markets. Our paper extends that literature by relaxing the assumption that stations are symmetric, and allowing instead for endogenous station differentiation along both horizontal and vertical dimensions. Importantly, we allow station quality to be an unobserved station characteristic. We compute the optimal market structures in local Radio markets and find that, in most broadcasting formats, a social planner who takes into account the welfare of market participants (stations and advertisers) would eliminate 50%-60% of the stations observed in equilibrium. This finding is robust to whether we consider horizontal differentiation only, or both horizontal and vertical differentiation. The rate of elimination is similar for high quality and for low quality stations. In 80%-94.9% of markets that have high quality stations in the observed equilibrium, welfare could be unambiguously improved by converting one such station into low quality broadcasting. In contrast, it is never unambiguously welfare-enhancing to convert an observed low quality station into a high quality one. This suggests (local) over-provision of quality in the observed equilibrium.

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# 1 Introduction

A vast theoretical literature (e.g., Spence (1976)) shows that free entry equilibria may result in inefficient market structures. The inefficiency may manifest itself in the number, variety, or quality of offered products. In the Radio industry, various authors (Steiner 1952, Rogers and Woodbury 1996) have argued that inefficient content duplication and excessive station entry may be prevalent. Berry and Waldfogel (1999, hereafter BW99) demonstrated such excessive entry empirically in a framework that did not allow for systematic station differentiation.

In this paper, we extend the literature by introducing observed and unobserved product-level differentiation into the empirical study of excessive entry. To the degree that horizontal differentiation is important, early estimates of excess entry may be overstated. Allowing for vertical differentiation is also important, as it allows us to empirically address questions regarding quality provision in an oligopoly equilibrium, an area in which obtaining theoretical predictions is difficult. Our empirical treatment of vertical differentiation is novel, allowing it to be an *unobserved station characteristic*. From an econometric standpoint, we deal with product differentiation via a particularly simple application of recently popular "bounds" methods for treating fixed costs in the presence of multiple equilibria.

Excessive entry may obtain if firms incur substantial fixed costs, and offer products that are close substitutes to one another (Mankiw and Whinston 1986). Firms continue to enter the market as long as their private gains exceed fixed costs, ignoring the negative externality associated with their entry, i.e., the reduction of rivals' output. In the context of local Radio markets, if stations offer similar content, entrants would mostly "steal business" from other stations, while incurring additional fixed costs, resulting in excessive entry. On the other hand, if stations offer differentiated content, additional stations may help expand the market, creating positive externalities. Such positive externalities may offset the additional fixed costs, in which case additional entry may be socially beneficial.

We find that a social planner who maximizes the joint surplus of stations and advertisers would like to reduce the number of stations by about 50%. This finding is robust to the dimension of differentiation considered, i.e., whether we allow for horizontal (format) differentiation only, or for both horizontal and vertical differentiation. Our findings can be contrasted with the 74% desired reduction in the number of stations reported in BW99. The smaller elimination rate in our paper may imply that accounting for station differentiation softens, to some extent, the excessive entry finding. Our findings also suggest that the elimination rate is quite uniform across broadcasting formats, as well as across different station quality levels. Since listeners do not pay for Radio content, quantifying their surplus in monetary terms is not possible.

Our framework also allows us to shed light on equilibrium quality choices and their properties. The theories of quality choice are well developed for the monopoly case (Mussa and Rosen (1978), Maskin and Riley (1984)), but much less so for the oligopoly case.[1] The difficulty of obtaining theoretical results in oligopoly equilibria has motivated empirical work on this issue, such as Mazzeo's (2002) analysis of quality choices in the motel industry. Compared to a Mazzeo's motel data, the quality of a radio station is more difficult to ascertain from observed data. We therefore pursue an approach that treats quality as an unobserved station characteristic, and provide methods to identify and estimate a model with such unobserved vertical differentiation.

A striking result from our analysis is that, in 80%-94.9% of markets in which we determine the presence of high-quality stations, welfare could be unambiguously improved by converting one such high quality station into a low quality. In contrast, it is never unambiguously welfare-enhancing to convert an observed low quality station into a high quality one. This analysis suggests that over-provision of quality, in a local sense, characterizes free-entry equilibria in radio markets.

**Methodology.** We base our analysis on a two-stage model. In the first stage, a large number of (ex-ante identical) potential entrants decide whether to enter the market, and in which format (or format-quality combination) to operate. The market structure determined in this first stage is, therefore, a vector describing the numbers of stations operating in each format (or format-quality cell). This can be contrasted to the market structure in the classic entry model of Bresnahan and Reiss (1991) (hereafter BR91) and in BW99, which is a scalar: the total number of firms that entered the market. The post-entry asymmetry implies that, unlike in BR91 or BW99, the market structure in the current paper is not uniquely determined in equilibrium.

In the second stage, entering stations pay fixed entry costs and garner revenues. Our model determines those revenues as follows: a discrete-choice model of listeners' preferences determines, given the market structure, how many listeners are captured by each station. Those listeners are then "sold" to advertisers at a price which is determined from a simple model of advertisers' demand for listeners. A station's revenue is, then, the product of the per-listener price paid by advertisers, and its total number of listeners.

Our discrete-choice model of listener choices builds on the nested logit model. We consider two specifications: one that allows for horizontal station differentiation only ("base case"), and one that allows, in addition, for quality differentiation in key formats: the largest music format, and the popular "News/Talk" format. Estimation of the model in the "base case" is rather simple, following a 2SLS strategy from Berry (1994) that accounts for endogeneity issues. The estimated model suggests that horizontal differentiation is a key determinant of listeners' utility. In particular, utility coefficients on both format dummy variables, and on interaction terms between format and demographic effects (e.g. the percentage of Hispanic population and the "Spanish" radio format) have a strong and statistically significant effect.

Estimation of the listening model specification that allows for both format and quality differ-

[1] For an example of such work, see Rochet and Stole (2002).

entiation is more complicated. We contribute to the literature by showing how to estimate such a model, overcoming the following challenges: first, the fact that quality is unobserved requires us to assign it within the estimation procedure. Second, quality choices are endogenous, an issue that we address with fixed effects that control for unobserved taste shocks at the market-format level. Third, the presence of these fixed effects complicates the estimation of the model substantially, and we propose a two-step estimator that overcomes this complexity.

We also estimate advertisers' demand for listeners, modeled by a simple constant-elasticity specification in which the advertising price depends on the total "output" of listeners. This model is estimated via 2SLS. The estimated model implies a downward-sloping demand curve with a constant elasticity of about $(-2)$, a similar value to that reported in BW99. Put together, the estimated listening equation and the advertisers' demand equation allow us to predict the revenue garnered by each station given any counterfactual market structure.

These revenue predictions allow us to estimate fixed costs, relying on necessary equilibrium conditions from the entry model described above. Suppose, for example, that three stations are observed to operate in the "Rock" format in a given local market. For this to be an equilibrium, it has to be the case that three stations are still profitable, while a fourth entrant would incur a loss. The first condition places an upper bound on the fixed cost of operating a Rock station in this market: the revenue of a Rock station in the observed market equilibrium. The second condition places a lower bound on this fixed cost: the revenue of a counterfactual, fourth entrant into the Rock format. Having estimated the listening equation and advertisers' demand as explained above, these revenue figures are easily computed and provide bounds on the relevant fixed cost.

The extant literature typically proceeds by utilizing these bounds on the fixed costs to estimate the distribution of fixed costs across markets. In BW99, these bounds were utilized, along with a parametric assumption on the distribution of fixed cost, to generate an ordered probit estimator of the parameters of this distribution. This point-identification approach is more problematic here since the potential non-uniqueness of equilibria prohibits us from writing down the likelihood function. To address this issue, the literature offers the possibility of estimating bounds on the parameters of the distribution of fixed costs using moment inequalities.[2] These estimators are often technically demanding and sometimes rely on strong parametric assumptions.

In this paper we take a different approach: instead of using the bounds on fixed costs of operation in different markets to estimate the distribution of fixed costs across markets, we use the market-specific bounds directly in our welfare analysis. This has two benefits: first, we do not have to make parametric assumptions on the distribution of fixed costs across markets (nor do we have to assume that costs are independent across such markets). Second, by not estimating the distribution of fixed costs, we avoid the difficult task of making inference on this distribution.[3]

[2] Some examples include Ishii (2008), Ho (2009), Crawford and Yurukoglu (2011), Eizenberg (2013).

[3] See, for example, Chernozhukov, Hong, and Tamer (2007), Pakes, Porter, Ho and Ishii (2011), Andrews and Jia (2012).

Our paper offers some additional methodological contributions that may be applicable in many empirical studies of market structure. We develop an algorithm that computes the optimal market structure in an environment where stations are discretely differentiated along horizontal and vertical dimensions. Our modeling of station unobserved quality, and the two-step estimation for the listening model that incorporates this quality differentiation, are also novel.

**Relationship to previous literature on the radio industry.** Several features make the radio industry an attractive arena to study product positioning in an oligopoly equilibrium. First, data is available from a large cross-section of local markets characterized by substantial variation in market population and listener demographics. Second, the nature of horizontal differentiation is easy to define and measure, since stations belong in well-defined broadcasting formats.

A couple of papers rely on reduced-form techniques to study the impact of mergers on broadcasting variety. Berry and Waldfogel (2001) document that the merger wave that followed from the 1996 Telecommunication Act reduced station entry but increased the variety of offered programming. Sweeting (2010) uses playlist data to study how station merger decisions affect positioning, and finds that, following a merger, owners of merging stations tend to push them apart (in characteristics space) to limit cannibalization, but at the same time reduce the extent of differentiation with respect to competitors.

Another line of research studies the market structure in the Radio industry via the estimation of a dynamic oligopoly game (Jeziorski (2012, 2013a, 2013b), and (Sweeting 2013)). Dynamic models are obviously better when considering explicitly dynamic questions. For example, Sweeting's (2013) dynamic analysis emphasizes the estimation of repositioning costs of existing stations. On the other hand, the current state of estimation techniques for dynamic oligopoly requires many strong assumptions. We view the static modeling pursued in our paper as complementary to these dynamic models, especially when the questions at hand are not explicitly dynamic.

The static approach determines the cross-section of equilibrium market structures as a function of long-run conditions in each market, captured in our case by the local market's population and its socioeconomic and demographic makeup. This leads to a simple and transparent setup to study the possibility of excessive entry, a question motivated both by theory, and by previous studies of the radio industry cited above. Pursuing a static model has a couple of additional benefits in our setup: first, it makes our analysis conceptually comparable to BW99's analysis, allowing us to explore the impact of relaxing symmetry assumptions and admitting multiple equilibria. Second, we are able to avoid making a parametric assumption on our key primitive, the distribution of fixed costs.[4]

The remainder of this paper is organized as follows: Section 2 describes the data and station

[4]Smith and O'Gorman (2008) study (independently from our work) the distribution of fixed costs in the radio industry relying on a static model and a partial identification approach. That paper pursues very different questions compared to our paper. In particular, we focus on questions that pertain to product variety, develop tools that compute optimal market structures, and address unobserved vertical differentiation issues.

format classifications. Sections 3, 4, and 5 describe the various components of our estimated model. Section 6 uses the estimated model to analyze the discrepancy between the free-entry equilibrium and the optimal market structure, and Section 7 concludes.

## 2 Data

The data used in this study cover a cross-section of metropolitan Radio markets in 2001. Market definitions follow those of Arbitron, a media marketing research firm that tracks activity and trends in the Radio industry. While some of Arbitron's 286 Radio markets coincide with Census MSA definitions, others do not.

Data regarding stations and listenership in these markets is obtained from the Spring 2001 edition of *American Radio*, by Duncan's American Radio. Rich information regarding individual stations is available from this source. We observe each station's "AQH-listeners," i.e., the number of listeners of age 12 and above who listened to the station during the average quarter-hour in Spring 2001.[5] These listenership figures are provided by Arbitron based on diaries retrieved from surveyed individuals in each market. We also observe whether the station is considered "home to the market," and its broadcasting format, which plays a key role in our analysis. At the market level, we observe the market's 12+ market population, and the total number of diaries retrieved by Arbitron. The number of retrieved diaries is related to the accuracy of the listenership data. In one of our empirical specifications reported below, we use this information to take into account the potential measurement error in stations' reported market shares.

We compute the market share of each station by dividing the number of its AQH-listeners by total market 12+ population. The share of the "outside option" of not listening to commercial Radio is computed as 1 minus the sum of stations' individual shares. Non-commercial stations (e.g., public Radio), as well as commercial stations not listed by Arbitron (e.g., due to very low listening, or due to violation of Arbitron's rules), are included in this outside option.

Additional market-level data were obtained from *Duncan's Radio Market Guide*. The 2002 edition provides estimates of each market's total revenue in 2001 (i.e., the combined annual revenue of all stations in the market). These figures are derived from a variety of sources. While some estimates are based on actual information provided by Radio stations to their accounting firms (or directly to Duncan's Radio Market Guide), other estimates are based on Duncan's assessments. Similarly as in BW99, we compute the market's *ad price*, i.e., the average price paid by advertisers for an AQH-listener, by dividing total market revenue by the total number of listeners to in-metro stations.[6]

[5]This average is computed over all quarter-hours in the standard survey week: Monday-Sunday, 6AM - 12 Midnight.

[6]This calculation assumes that all of the market's revenue is garnered by in-metro stations, i.e., stations that are home to the market. This assumption could be put into question in markets where substantial listenership is enjoyed by out-metro stations. For example, the extreme ad price of $2691 reported in Table 1 below occurs at Bridgeport, Connecticut,

An alternative approach to using total market revenue data, pursued recently by Sweeting (2013) and Jeziorski (2012, 2013a, 2013b) utilizes station-specific data obtained from different sources than those we use here. These station-specific revenue data are computed using various assumptions based on proprietary methodology of the data provider. Our approach has both advantages and disadvantages: while it forces the ad price to be identical across different formats, it also avoids the potential measurement error stemming from the methodology used to assign station-specific revenue numbers. Ultimately, we stick with the total market revenue figures, in part because of our interest in staying conceptually close to the methodology used in BW99.

The 2001 edition of Duncan's Radio Market Guide provides market-level demographic information for the year 2000. In particular, the market's percentage of Black and Hispanic population, average income, and percentage of college-educated is available. We have full data (including revenue and demographic information) for 163 of Arbitron's 286 markets, and we restrict our analysis to those 163 markets. After dropping observations (stations) with reported zero listenership, the data we use cover 4,362 stations in the included markets. Finally, we classify markets into geographic regions (Northeast, Midwest, South, and West) based on Census definitions.

Summary statistics on some of the market-level variables are available in Table 1. The mean listenership share (i.e., the share not choosing an outside option) is about 12%. The average market has 19.6 in-metro stations, and 7.2 out-metro stations. The average ad price is 570 Dollars. Since annual revenue was used to compute this price, as explained above, this number pertains to the average price paid for one listener over the course of one year.

**Format classification.** Stations' broadcasting formats represent horizontal differentiation and, therefore, play an important role in our analysis of variety in Radio markets. The number of different formats in the data is close to 70, motivating an aggregation into higher-level categories. We classify formats into ten such categories, based on intuition gained from a large number of sources about the nature of the formats. The ten format categories are described in Table 2.

Some idea on the performance of these format categories is provided in Table 3. The "Frequency" column describes the share of markets where a given category is represented by at least one (in-metro or out-metro) station. Three format categories raise potential selection issues: "Religious" stations are present in about 80 percent of the markets, while "Urban" and "Spanish" are present in 74 and 40 percent, respectively. Econometric implications of this issue are addressed below. Additional columns of Table 3 reveal that the most popular format (in terms of total format listening share, on average across markets) is "Mainstream", followed by "Rock", "Country" and "News/Talk."

a market heavily served by out-metro stations. This assumption, however, may be justified even for such markets: it may be costly for a local advertiser to reach the local audience when the market is heavily served by out-metro stations, and the relatively high ad price may reflect that.

# 3 Listening Model

The model has three components. The first component, described in this section, is the listening equation which determines stations' market shares as a function of listeners' tastes, conditioning on a given market structure. The second component, described in the following section , models the other side of this media market: advertisers' demand for listeners. Together, the listening function and the advertisers' demand function determine stations' revenues given any fixed market structure. The market structure itself is determined by the third component of the model: the entry game, described in its own section.

The listening equation builds on a nested-logit specification. We estimate two listening models: the first, described in subsection 3.1, allows for horizontal (format) differentiation only. The second model, described in subsection 3.2, extends this analysis by incorporating unobserved quality differentiation in two important formats.

## 3.1 A listening equation with horizontal differentiation

Our first listening model captures format horizontal differentiation in a standard nested logit model. The model has 11 nests: a single nest for each of the ten format categories, and an additional "outside option" nest. Listener $i$'s utility from listening to station $j$, which belongs to format category $g$, in market $t$, is given by:

$$u_{ijt} = \delta_{gt} + \nu_{igt}(\sigma) + (1-\sigma)\epsilon_{ijt}, \text{ with } \delta_{gt} = x_{gt}\beta + \xi_{gt} \tag{1}$$

where $x_{gt}$ is a vector of format and market characteristics, and includes the average income, the share of college educated, the shares of Black and Hispanic population, dummy variables for geographic regions and for format categories, and some intuitive interaction terms (for instance, an interaction between the share of Hispanic population and the Spanish broadcasting format). The unobserved term $\xi_{gt}$ shifts the mean taste toward format $g$ in market $t$, while $\nu_{igt}(\sigma)$ is an idiosyncratic taste of listener $i$ toward format $g$, and has a unique distribution derived by Cardell (1997), which depends on the parameter $\sigma$. The shock $\epsilon_{ijt}$ is an idiosyncratic taste of listener $i$ toward station $j$ in market $t$, assumed to follow a Type-I Extreme Value distribution.

Note that the "mean utility" component, $\delta_{gt}$, is restricted to be identical within a given market-format data cell. This restriction is not dictated by estimation considerations: the appendix reports a robustness check in which this symmetry assumption is relaxed. Rather, this symmetry assumption simplifies counterfactual analyses in which stations enter and exit a particular format, since it allows one to compute a well-defined mean utility for any such station.

In practice, the within-format symmetry is modified slightly to account for an important feature of the data: stations' "in-metro" vs. "out-metro" status. Our results indicate that this feature is an important determinant of market shares. To account for this, we assume symmetry among all in-metro stations in the format, as well as among all the out-metro stations in the format. We therefore have two distinct mean utility levels within the market-format: $\delta_{gt,in-metro}$ and $\delta_{gt,out-metro}$. We also include an in-metro (or, "home") dummy variable in the $x$ covariate vector. For simplicity, the notation above (as well as in other parts of the paper) does not reflect the distinction between in-metro and out-metro stations.

While mean-utilities are symmetric, individual stations within the format are still allowed to bring unique benefits via the $\epsilon_{ijt}$ term. The extent of such effects is determined by the estimated parameter $\sigma$, which captures the degree of within-nest correlation in unobserved individual tastes. As $\sigma$ approaches 1, the unobserved tastes of any individual listener toward stations within the same format become near-perfectly correlated, leading to strong "business stealing" within the format. In contrast, Cardell's unique distribution guarantees that, as $\sigma$ approaches 0, $\nu_{igt}$ approaches zero as well, implying no correlation in unobserved tastes within the format and a convergence to the simple logit model. This extreme case corresponds to maximal diversity in the content provided by stations within the format.

Estimating $\sigma$, therefore, is a key task for our empirical framework: in light of the discussion in the introduction, the value of $\sigma$ informs us about the scope of business stealing and potential excessive entry. The simple association of the $\sigma$ parameter with "business stealing" is an advantage of the nested logit framework in this context.

**Estimating the listening equation** Following Berry (1994), the nested logit specification leads to a linear estimation equation for station $j$, operating in format $g$ in market $t$:

$$ln(s_{jt}) - ln(s_{0t}) = x_{gt}\beta + \sigma ln(s_{j/g,t}) + \xi_{gt} \tag{2}$$

where $s_{jt}$ is the market share of station $j$, $s_{j/g,t}$ is the share of this station as a fraction of the total listening share to format $g$ in market $t$, and $s_{0t}$ is the share of the outside option. The within-nest symmetry in mean-utility levels implies that stations of a given format are predicted to garner identical market shares. This means that $s_{jt}$ should be calculated as $S_{gt}/N_{gt}$, where $S_{gt}$ and $N_{gt}$ are the observed total market share and total number of stations in the market-format cell, respectively. Similarly, the fraction $s_{j/g,t}$ should equal $(1/N_{gt})$. In practice, however, the differentiation of in-metro vs. out-metro stations leads to slightly different calculations: for example, we obtain the share of a typical in-metro station in format $g$ by dividing the total observed share of *in-metro* stations in format $g$ by the total number of such in-metro stations.

The symmetry assumption further implies that we only retain (at most) two observations for each market-format data cell: an observation pertaining to the typical in-metro station in this format-market, and an observation pertaining to the typical out-metro station. Since it is possible that there are no in-metro stations, or out-metro stations, in the format-market cell, the number of observations pertaining to this format-market may in fact be zero, one or two.

**Challenges: Endogeneity and Selection** The term multiplying the correlation parameter $\sigma$ in (2) is endogenous, motivating estimation via two-stage least squares. Three excluded instruments are used: the market population, the number of out-metro stations in the market, and the number of out-metro stations in the market-format cell. The presence of out-metro stations is assumed to be exogenous to market conditions, and, in particular, to be uncorrelated with the taste shock $\xi$. At the same time, their number does affect market shares, and so it is correlated with the endogenous variable. As in BW99, market population affects entry decisions, making it an effective instrument for market shares.

A more difficult challenge is sample selection, which, as discussed above, is a relevant concern for the Urban, Spanish and Religious formats. One may suspect that we only observe such stations in markets where the unobserved taste for such broadcasting is sufficiently strong, leading to an upward bias in the estimates of the coefficients on the relevant format dummy variables. Addressing such selection problems in the context of a product-choice model with complete information is quite complicated, since the selection mechanism depends on the error terms of all products (rather than on the error of the specific product), and is not uniquely determined in equilibrium. Following traditional selection-correction mechanisms, such as Heckman (1976, 1979), is infeasible.

Eizenberg (2013) offers a partial-identification strategy to formally address the product selection issue in a study of product choices in the PC industry. In contrast, we do not formally address the selection issue within the estimation procedure. Instead, we offer in the appendix several analyses of the robustness of our results to the selection issue. First, we demonstrate that the presence of stations in the Urban and Spanish formats is very strongly driven by observables for which we control—namely, the demographic makeup of the market's population. Second, we re-estimate our model using a sub-sample of markets that are predicted to have stations in the relevant format (e.g., Urban) with a very high probability. This subsample should be viewed as selection-free to a large extent. Our results indicate, reassuringly, that the estimates do not change in a way that is consistent with sample selection bias (though the evidence is consistent with some degree of selection bias in the case of the Spanish format).

**Estimation results** Table 4 provides the results of estimating the listening model described above. The variables that have the strongest impact on a station's listenership are the dummy variables for in-metro status and for format categories, and the interactions of the format and the demographic effects. These effects are very precisely estimated. As expected, popular formats such as Mainstream or Rock have large estimated coefficients in this specification. Also expected is the strong and significant effect of the interactions between the fraction of Black population and the Urban format, the interaction between the fraction of Hispanic population and the Spanish format, and the interactions of the South region dummy with the Religious and Country formats. The fraction of the market's population with college education is negatively related to listenership. Finally, the correlation parameter $\sigma$ is estimated at 0.519.

### 3.2 Horizontal and vertical differentiation

Our second listening model augments the dimension of the discrete product space: in addition to horizontal format differentiation, stations are now allowed to vertically differentiate by choosing their broadcasting quality. To maintain a discrete entry space, we model quality as discrete. This creates a set of horizontal/vertical cells into which stations can enter. Although our arguments generalize to a larger number of discrete quality levels, we use only two levels for the unobserved discrete station quality of in-metro stations,"high" and "low."

How should one define and measure station quality? Our data offer, at best, some imperfect proxies for quality, such as the station's broadcasting wattage. A station's actual quality is likely to depend primarily on the quality of the content provided, a feature which is inherently difficult to quantify. As a consequence, we choose to model quality as an *unobserved* station characteristic that shifts listeners' mean utility. Stations' quality classifications are treated as discrete parameters to be estimated along with the other parameters of the model. An additional challenge is the endogeneity of quality: a station's quality choice may depend on the unobserved taste for its broadcasting format in the relevant market. We address this by including market-format fixed effects in the empirical specification. As a consequence of those challenges, estimation becomes more complicated compared to the base model where only horizontal differentiation is allowed.

The utility for listener $i$ from listening to station $j$ in format $g$, in market $t$ is assumed to have the usual nested logit structure we defined before,

$$u_{i,j,t} = \delta_{jt} + \nu_{igt}(\sigma) + (1-\sigma)\epsilon_{ijt}, \tag{3}$$

with "mean utility" for station $j$ now given by

$$\delta_{jt} = \gamma^q \cdot q_{jt} + \gamma^h \cdot h_{jt} + \psi_{gt}. \tag{4}$$

In the mean utility, $q_{jt}$ is the quality level of a station, $h_{jt}$ is a "home" dummy variable for in-metro stations and $(\gamma^q, \gamma^h)$ are parameters to be estimated. As noted, the quality levels are for simplicity assumed to take on only two values: 0 ("low") and 1 ("high"). The term $\psi_{gt}$ is a format-market fixed effect, capturing the mean taste for format $g$ in market $t$. This depends in turn on both observed and unobserved components,

$$\psi_{gt} = d_{gt}\lambda + \xi_{gt}, \tag{5}$$

where $d_{gt}$ is a vector of observed variables, $\lambda$ is parameter to be estimated and $\xi_{gt}$ is still the unobserved listener taste for format $g$ in market $t$.

Since quality is unobserved, the values of the high-quality dummies $q_{jt}$ are also parameters of the model. For simplicity, we impose the restriction that quality differentiation only applies to in-metro stations in the market, so that $q_{jt} = 0$ whenever $h_{jt} = 0$. We thus have three cells of stations within each format-market pair: out-metro, in-metro low-quality, and in-metro high-quality stations, with respective quality levels of 0, $\gamma^h$ and $(\gamma^h + \gamma^q)$. Mean utilities, and hence expected market shares, are predicted to be identical within each of these three cells. The restriction that out-metro stations offer low quality has empirical implications: it orders predicted market shares such that, as long as $\gamma^h$ and $\gamma^q$ are positive, out-metro stations have lower predicted shares than in-metro low-quality stations, which in turn have lower shares than in-metro high-quality stations. Since out-metro stations do typically have lower shares than in-metro stations, we view this as a reasonable and useful simplification.

### 3.2.1 Identification of the Horizontal-Vertical Model

We begin by considering identification when the expected market shares are perfectly observed – that is, there is no sampling error due to the Arbitron listener diaries. We can think of this as an approximation to the case where there are very many sampled listeners in every market. We assume throughout that $\gamma^h$ and $\gamma^q$ are positive and so the shares of high quality in-metro stations are higher than low quality. Thus, in any market where we see two distinct market share values for in-metro stations, the higher market share implies high quality and the lower share implies low quality.[7]

When market shares are equal for all in-metro stations, identification is harder. The reason is the confounding effect of the market-format taste terms $\psi_{gt}$. Consider a market where all the in-metro stations have the same market share within some format. For any guess at the quality level of stations in the market, there is a value of $\psi_{gt}$ that explains the observed common level of shares.

Because the market-format taste does not effect the within format shares, we can avoid this potential problem of non-identification if we focus on the within format shares. This is similar to the idea of "differencing out" a fixed effect to deal with endogeneity. To proceed, let

$$\begin{aligned} \kappa_1 &\equiv \gamma^q/(1-\sigma), \qquad (6) \\ \kappa_2 &\equiv \gamma^h/(1-\sigma), \end{aligned}$$

and let the vector $\kappa \equiv (\kappa_1, \kappa_2)$. The nested logit then implies that conditional on choosing format $g$ the expected probability of choosing station $j$ in market $t$ (the "within format share") is given

[7] If we could perfectly observe in-metro expected market shares and we found these took on more than two levels, then we could reject the model with only two qualities for in-metro stations.

by

$$p_{j/gt}(\kappa, q) = \frac{exp(\kappa_1 \cdot q_{jt} + \kappa_2 \cdot h_{jt})}{\sum_{\ell \in g} exp(\kappa_1 \cdot q_{\ell t} + \kappa_2 \cdot h_{\ell t})}, \tag{7}$$

where $q$ is notation for the long vector of quality levels for all markets' stations. Of course, the expression in (7) depends only on the quality levels in the given market-format.

This expression for within format shares allows us, first, to identify $\kappa$ using data on markets where differences in shares identify quality levels. We can then use $\kappa$, together with out-metro shares, to identify quality levels in additional markets. In particular, we can identify $\kappa$ from a single market $t$ with two in-metro stations ($j$,$k$) in format $g$ such that $s_{jt} > s_{kt}$. Because the shares are different, we know that $q_{jt} = 1$ and $q_{\ell t} = 0$. A simple manipulation of the nested logit share equation then identifies $\kappa_1$ as

$$\kappa_1 = ln(s_{jt}) - ln(s_{kt}).$$

Performing a similar exercise with two stations such that $q_{jt} = 0, h_{jt} = 1, h_{\ell t} = 0$ (i.e., $j$ is known to be a low quality in-metro station, while $\ell$ is an out-metro station), identifies $\kappa_2$:

$$\kappa_2 = ln(s_{jt}) - ln(s_{\ell t}).$$

Given $\kappa$, we can then identify the quality level for in-metro station $j$ in format $g$ in any market $t$ that has an out-metro station, denoted $\ell$, in that same format. As usual, the nested logit structure delivers the following equation for station $j$:

$$ln(s_{jt}) - ln(s_{0t}) = \gamma^q q_{jt} + \gamma^h h_{jt} + \psi_{gt} + \sigma ln(s_{j/g,t}).$$

Writing the same expression for station $\ell$ and subtracting one from the other leads to:

$$q_{jt} = \frac{1}{\kappa_1} ln\big(s_{jt}/s_{\ell t}\big) - \frac{\kappa_2}{\kappa_1}.$$

This gives us identification of quality whenever there is an out-metro station. Since we treat the presence of out-metro stations as exogenous, we have an exogenously chosen sample of markets where station-level quality is identified.

Since we trivially have identification of quality whenever in-metro stations have different shares, this leaves us with one remaining case of partial identification: market/formats with no out-metro station and identical shares for in-metro stations.[8] In these market/formats, we know that either [i] all stations are high quality or [ii] all stations are low quality. In the sections on estimation and counterfactual simulation below, we discuss how we approach this issue of partial identification

[8]The case of "identical shares" obviously includes the case where there is only one in-metro station in the market/format.

in some market/format pairs.

Note that having identified qualities, we move back to the usual case of Berry (1994) with a nested logit where all characteristics are observed (although recall that the unobservable taste variable $\xi_{gt}$ is at the level of the format, not station.) Thus, the remainder of the demand identification problem is standard and we will continue to need an instrument variables approach to identify $(\gamma^q, \gamma^h, \sigma)$ separately, as opposed to the composite parameters $(\kappa_1, \kappa_2)$ that are identified from the within format choice problem. The procedure that implements this approach in practical estimation is reviewed in the next subsection.

#### 3.2.2 Estimation of the Horizontal/Vertical Model

Analogous to the identification argument, we consider estimation in two steps. First, we estimate $(\kappa, q)$ from the within group shares. Second, we use a more classic IV method to estimate the remaining parameters.

**Step 1: estimating quality levels** Moving from identification to estimation, we face the problem that we do not observe expected market shares, but only sampled shares computed from the Arbitron diaries. The sampling error means that we cannot directly observe whether expected shares are equal or not. Indeed, even when expected shares are exactly equal, we are exceedingly unlikely to observe $s_{jt} = s_{\ell t}$ for two stations $j$ and $\ell$. However, the observed Arbitron shares are a draw from a multinomial distribution with known properties, so for estimation we can employ a maximum likelihood approach. In particular, to estimate quality we consider maximum likelihood estimation based on the within format shares where, since $\psi_{gt}$ drops out, the only sampling error is from the Arbitron diaries and the endogeneity problem of potential correlation between quality and unobserved taste is not present.

Denote by $n_{jt}$ the number of Arbitron diaries reporting listenership to a given station.[9] The log-likelihood for the within group choices, conditional on choice of format, is then

$$log\mathcal{L}(\kappa, \kappa, q) = \frac{1}{\overline{N}} \sum_t \sum_g \sum_{j \in gt} n_{jt} \cdot log\left[p_{j/gt}(\kappa, q)\right] \tag{8}$$

To derive the asymptotic behavior of the ML estimates, we take the total number of Arbitron diaries,

$$\overline{N} = \sum_t \sum_{j=0}^{J_t} n_{jt}$$

to infinity, holding fixed the relative sample sizes in each market.

The discrete quality parameters $q$ raise issues of both estimation and computation. There is

[9] Strictly speaking, this is the number of diaries reporting listenership to the station in the average quarter-hour, see Section 2.

one quality parameter per station, but this is not a problem since there are a large number of diary responses per station. Our estimates are consistent, by usual arguments, as the number of sampled diaries goes off to infinity. Indeed, since each quality parameter is discrete, taking on only two values, by usual arguments the estimate of quality is super-efficient – it converges faster than rate $\sqrt{N}$. In contrast, $\kappa$ converges at the usual rate.

There is also the computational issue of maximizing the likelihood over the large number of possible combinatoric assignments of quality. First note that, conditional on $\kappa$, the quality assignment breaks up across market/formats—the assignment of quality in one market/format does not affect the likelihood contribution of other market/formats. Second, as long as $\gamma^q > 0$, in any market/format a high-quality station has a higher predicted market share than a low-quality station. It is easy to show that if the maximum likelihood estimate of $q$ assigns a high quality to given station $j$, it also assigns high quality to all stations with observed sample shares larger than $j$. Thus, the problem of estimating the quality vector for any market/format reduces to the problem of choosing the threshold station: the station with the largest observed share that still corresponds to a low quality station. We denote the index of this threshold station by the discrete parameter $j'_{gt}$. If $j'_{gt} = 0$, all in-metro stations in the market-format pair offer high quality. If this index is equal to the number of such in-metro stations, all those stations offer low quality.[10] If there are $J_{gt}$ stations in market/format $(g, t)$ then conditional on a value of $\kappa$ we have to compute the likelihood only $J_{gt} + 1$ times to choose the best value for the threshold $j'_{gt}$.

The analog of the partial identification problem discussed above arises in the estimation context for market/format pairs that have no out-metro stations. In all of these market/formats, and for each value of $\kappa$, setting $j'_{gt}$ equal to either zero (implying that all stations offer high-quality) or to the number of in-metro stations (implying that all stations offer low-quality) yields the same value for the log-likelihood contribution of the market-format. If that is also the value that maximizes the likelihood, then we have a set estimate of the qualities of stations in this market-format pair: the maximized likelihood is generated by the case where the stations are all of high quality and by the case where all are of low quality.

Importantly, because the ML objective function obtains the same value whether we assign the unclassified stations to be of high quality, or of low quality, our ML estimates for $\kappa$ are unaffected by the set estimates of quality. However, the "IV" estimates of $(\gamma^q, \gamma^h, \sigma, \lambda)$, discussed below, will be affected by the allocation of all stations to either high or low quality. We discuss strategies to deal with this below.

**Step 2: estimating the remaining parameters via a restriction on the distribution of $\xi$.** Having obtained estimates of $(\kappa, q)$, we now hold these fixed and proceed with estimating the remaining parameters of interest. Given $\kappa$ and $\sigma$ we can solve for $(\gamma^q, \gamma^h)$ from (6) so we can

[10] Note the slight abuse of notation, made for convenience: here we use $j$ to index stations within the market/format pair, whereas elsewhere we use it to index stations in the entire market.

treat the "business stealing" parameter $\sigma$, together with the format taste parameters $\lambda$ in (5), as the only remaining unknowns. As explained below, to ensure that we have point-estimates of quality for all market/formats, our base case estimation allows for quality differentiation in only a subset of formats and, for those formats, uses only the exogenously selected sample of market/formats with out-metro stations.

As in the pure horizontal model, we assume that the unobserved format-level taste shifter in equation (5) is mean-independent of a set of instruments,

$$E[\xi_{gt}|Z_{gt}] = 0. \tag{9}$$

In the empirical application, we let $Z_{gt}$ contain the market's population, the number of the market's out-metro stations, and the number of out-metro stations in the same format, as well as the $d$ covariates.

A crucial step is to note that, given $(\kappa, q, \sigma)$, there is a unique vector of fixed effects $\psi$ that maximizes the overall multinomial log-likelihood of the observed shares. Further, there is a closed form solution for $\psi$. See Appendix C for a proof that

$$\psi_{gt}(\kappa, q, \sigma) = log(s_{gt}) - log(s_{0t}) - (1-\sigma)log[\sum_{j\in g} e^{(\kappa_1 q_{jt} + \kappa_2 h_{jt})}]. \tag{10}$$

This further suggests that, given candidate values for $(\sigma, \lambda)$, and the fixed estimates $(\hat{\kappa}, \hat{q})$ obtained in step 1, we can solve for the unobserved taste shifter $\xi_{gt}$ as

$$\xi_{gt}(\hat{\kappa}, \hat{q}, \sigma, \lambda) = \psi_{gt}(\hat{\kappa}, \hat{q}, \sigma) - d_{gt}\lambda$$

The mean-independence condition (9) now motivates estimating $(\sigma, \lambda)$ by minimizing the following classic GMM objective function:

$$J(\sigma, \lambda; \hat{\kappa}, \hat{q}) = \left[\psi(\sigma, \hat{\kappa}, \hat{q}) - d\lambda\right]' Z\Phi Z' \left[\psi(\sigma, \hat{\kappa}, \hat{q}) - d\lambda\right].$$

where $\hat{\kappa}$ is the vector of the first-stage estimates which we hold fixed in this GMM estimation procedure, $d$ is a matrix whose rows are the $d_{gt}$ covariates, $Z$ is the instrument matrix, and $\Phi = (Z'Z)^{-1}$ is a weighting matrix.

This objective function can be further simplified by noting that, conditional on $\sigma$, it is possible to "concentrate out" the $\lambda$ parameters[11], allowing us to write down a GMM objective that can be maximized by searching over values of the scalar parameter $\sigma$ only:

$$J(\sigma; \hat{\kappa}, \hat{q}) = \left[\psi(\sigma; \hat{\kappa}, \hat{q}) - d\lambda(\sigma; \hat{\kappa}, \hat{q})\right]' Z\Phi Z' \left[\psi(\sigma; \hat{\kappa}, \hat{q}) - d\lambda(\sigma; \hat{\kappa}, \hat{q})\right] \tag{11}$$

[11] This is similar to the concentrating out of the "linear parameters" in Berry, Levinsohn and Pakes (1995) or Nevo (2000)

This second-step estimation yields the GMM estimates $(\hat{\sigma}, \hat{\lambda})$. Finally, estimates for the home and quality effects are now easily computed by $\hat{\gamma}^h = \hat{\kappa_2} \cdot (1 - \hat{\sigma})$ and $\hat{\gamma}^q = \hat{\kappa_1} \cdot (1 - \hat{\sigma})$, respectively.

**Dealing with set-estimates of qualities** We here provide further details on how we deal with the market/formats in which two different vectors of quality levels are equally consistent with the data. Note that there are many formats that feature a small number of stations, including a small number of out-metro stations. In these formats it is often not possible to point-estimate quality levels. Importantly, then, we restrict our endogenous unobserved quality differentiation to apply only to the main music format, Mainstream, and to the News/Talk format. Mainstream has the highest listening share among all ten formats while News/Talk is the leading non-music format. In these formats the quality assignment procedure seems to work robustly well. Stations in the other eight formats continue to offer a single quality level, as in the base analysis.

Even in these two formats, there are still market-format pairs where in-metro stations could not be assigned to a single quality level in step 1 of our estimation procedure. In particular, quality in the Mainstream format was undetermined in 44 out of the 163 markets (27%). In the News/Talk format, it was undetermined only in 17 markets (10.4%). It may be that quality differentiation is particularly pronounced in News/Talk. In market/formats with set-estimates of quality, we cannot compute the closed-form solution for $\psi_{gt}$ and cannot therefore cannot properly perform the GMM estimation step.

Our leading solution is a version of an "exogenous selection" procedure often used to overcome sample selection problems. Recall from our discussion above that, in the presence of an out-metro station, quality is assigned with probability 1. Eliminating from the GMM objective function market-format pairs that have no out-metro stations, therefore, leaves us with observations in which quality is always assigned. This approach leads to estimators that are robust to selection bias.[12] We therefore pursue this strategy as our leading specification. A total number of 180 out of 1,433 market-format pairs are dropped in practice, leaving us with 1,253 observations. We report below several robustness checks for this approach.

**Computing standard errors.** Standard errors for the first-step ML estimator of $(\hat{\kappa}, \hat{q})$ were obtained using the usual ML formulae. In practice, we only computed standard errors for $\hat{\kappa}$, and not for the many threshold quality parameters $\hat{j}'$, which converge at a faster rate. Standard errors for $(\sigma, \lambda)$, estimated in the second step, were corrected for the error stemming from the first-step estimation of $(\hat{\kappa}, \hat{q})$ using results for two-step estimation models (see Newey and McFadden (1986)). Those results require deriving the joint distribution of (i) the second-step GMM moment functions, and (ii) a linear expansion of the first-step ML estimator.[13]

[12] An alternative approach, which would remove only the market-format pairs where quality was actually unassigned, would not be robust to selection bias.

[13] Additional details are available from the authors upon request. We are grateful to Donald Andrews for his feedback on some aspects of these calculations. For simplicity, the computations were performed using all observations, rather than excluding observations from the 180 market-format pairs discussed above. Given that estimation results were reasonably robust to this exclusion, this issue is not likely to have a major impact on the estimated standard errors.

**Estimation results.** Table 5 presents estimation results for the listening model that allows for both horizontal and vertical differentiation. Panel A of this table presents the Maximum Likelihood estimation results for the parameters $\kappa$. This procedure has 4,362 observations, representing individual stations in the sample.

Panel B presents results obtained from the second step of our procedure, which holds fixed the estimated values of $(\kappa_1, \kappa_2, j')$ and estimates the parameters $(\sigma, \lambda)$ via GMM. An estimate of 0.589 is obtained for the correlation parameter $\sigma$. As expected, both $\gamma^h$ (the effect of in-metro status) and $\gamma^q$ (the effect of quality) are positively signed. The coefficients on the taste shifters are highly intuitive, with popular formats (e.g. Mainstream, Country, Rock) obtaining larger estimated coefficients than less popular formats. Also apparent is the natural role played by interaction terms. These patterns are very much in line with the findings from the "baseline specification" where quality differentiation was not allowed (see Table 4).

To examine robustness to our handling of the missing quality assignments, we consider three alternatives to the exogenous selection approach which led to the elimination of 180 market-format pairs that did not have an out-metro station. The first robustness check utilizes all 1,433 market-format pairs and sets all undetermined qualities to "low." This yields a value for $\sigma$ of 0.569, i.e., very close to the 0.589 from our leading specification. A second robustness check also keeps all market-format pairs, but sets all undetermined quality to "high." This yields a somewhat higher estimate for $\sigma$: 0.702. Finally, the third robustness check eliminates all observations pertaining to the Mainstream format. This leaves us with eight formats in which quality assignments are assumed to be fixed, and one format—News/Talk—in which quality assignment succeeds in close to 90% of markets. We set the unassigned cases to "low" quality. This yields an estimate for $\sigma$ of 0.503.

These robustness checks suggest that the estimates obtained from our baseline specification are reasonable, in addition to being theoretically justified by the exogenous selection approach. It is these estimates, therefore, that we carry forward to the remainder of the empirical analysis.

## 4 Advertisers demand for listeners

Having described the listeners' demand for programming, we now describe the second component of our framework: a model for advertisers' demand for listeners. Here, we face similar data issues to BW99 and we closely follow their approach. This model relates the price of advertising to the share of the population listening to in-metro stations, as well as to market characteristics such as demographic and regional effects. This model assumes that a station's revenue is proportional to the number of its AQH-listeners. Stations "produce" listeners and sell them to advertisers at a price, determined from an inverse demand curve that reflects advertisers' willingness to pay for listeners. The market-$t$ price is denoted $p_t$. Market $t$'s inverse demand curve is given by the following constant-elasticity specification:

$$\mathcal{P}_t = \alpha_t \times (S_t^1)^{-\eta} \tag{12}$$

where $\alpha_t$ is a market-specific constant, and $S_t^1$ is the total listening share to in-metro stations in market $t$. We further parameterize the log of $\alpha_t$ by $ln(\alpha_t) \equiv k_t\gamma + \omega_t$, where $k_t$ is a vector of market characteristics, and $\omega_t$ is an additive error term. Taking logs, and replacing the model's predicted ad price $\mathcal{P}_t$ by its empirical counterpart, $p_t$ (computed from data as explained in section 2 above), we obtain the following estimation equation:

$$ln(p_t) = k_t\gamma - \eta ln(S_t^1) + \omega_t \tag{13}$$

Estimation of this equation must take into account the endogeneity of the total in-metro share $S_t^1$: a high value for $\omega_t$ induces entry, which in turn increases this share. We instrument for this share using the market's population and its number of out-metro stations. Table 6 provides the results of estimating the model in equation (13) via 2SLS. Since the elasticity of demand is $-(1/\eta)$, the estimate of $\eta$ implies an elasticity of about (-2), a similar result to that in BW99. As can be expected, the ad price is positively correlated with higher metro income and education levels, implying that advertisers are willing to pay more for more affluent listeners.

Ideally, one would like to allow the ad price to vary not only across markets, but across listening formats as well. This would make sense since advertisers (and stations) are likely to internalize the fact that different formats target different consumer types. Data limitations prohibit us from pursuing such an approach.

## 5 The entry game and estimation of fixed costs

The discussion of the listener's utility model (subsection 3.1) and of advertisers' demand for listeners (subsection 3.2) was conditioned on a given market structure, that is: given numbers of stations operating in each market-format (or, market-format-quality) cell. We now turn to describing the third and final component of our framework: the entry game which determines this market structure. We assume that a large number of (ex-ante identical) potential entrants contemplate entry into each local Radio market. They engage in a two-stage game:

1. Potential entrants simultaneously choose whether to enter the market as an in-metro station and, if so, in which format category to operate (or, in the case that allows for vertical differentiation: in which format-quality combination to operate). Entering stations incur fixed costs that are specific to their market-format (or, market-format-quality) cell.

2. Entering stations produce listeners as described by the listening model, and sell them to

advertisers at a price which is determined from the inverse demand curve for listeners.

Notice that the only active decision modeled here is entry: once in the market, stations' market shares are determined by the listening equation, while the ad price charged to advertisers is determined from the inverse demand curve (12). The solution concept employed is complete information Nash equilibrium. Importantly, this is a "once-and-for-all" model in which stations make the correct decision of being in or out of the market (and, when in the market, in which format to operate).

The entry decisions determine market $t$'s structure, $N_t$. In the base analysis that only allows for horizontal differentiation, this is a ten-vector describing the number of in-metro stations in each of the ten formats. In the case that allows for horizontal differentiation as well, this could potentially be a 20-vector, but since we only allow quality differentiation in two formats, this is a 12-vector instead.[14]

A key feature of models where agents make simultaneous entry decisions into discrete market segments is that uniqueness of equilibrium is not guaranteed. Intuitively, the market may have one equilibrium in which two stations operate in format A and a single station operates in format B, and another equilibrium in which these numbers are reversed. The non-uniqueness implies that fixed costs of operation are only partially identified. We next explain how necessary equilibrium conditions provide such partially-identifying information.

**Bounds on fixed costs: the case of horizontal differentiation.** Let us begin by considering the base case where only horizontal differentiation is allowed. Our goal is to compute upper and lower bounds on $f_{gt}$, the fixed cost of operating a station in market $t$ and format $g$. We do not specify an equilibrium selection mechanism. We do assume, however, that the observed market structure constitutes *some* equilibrium outcome of the game described above. As a consequence, the following necessary conditions must hold: (i) no station operating in the market is making variable profits that are lower than its fixed operating costs, and (ii) no additional entrant could garner variable profits in excess of the operating fixed costs.

Note that the variable profit predicted by the model for a station operating in format $g$ and market $t$ is given by:

$$V_{gt}(N_t, d_t, \theta_0) = \mathcal{S}_{gt}(N_t, d_t, \theta_0) \times pop_t \times \mathcal{P}_t(N_t, d_t, \theta_0)$$

where $\theta = (\beta', \sigma, \eta)'$ are the model's parameters, $\theta_0$ denotes their true value, and $\mathcal{S}_{gt}(N_t, d_t, \theta_0)$ is the market share function which determines the share of a station in format $g$, market $t$ as a function of the market structure vector $N_t$, and of the market level variables $d_t$ (such as income, education and other demographics). This function is given by the nested-logit market

[14] While not reflected by this notation, recall that the actual market structure also includes the numbers of out-metro stations in all formats, which are taken to be fixed and exogenous.

share formula. The market's population is given by $pop_t$. The market's ad price, predicted from equation (12), is denoted $\mathcal{P}_t(\cdot)$.

We now compute bounds on $f_{gt}$ using necessary equilibrium conditions. Condition (i) implies that an upper bound is given by the variable profit actually garnered by stations operating in this format. This upper bound can be computed directly:

$$f_{gt} \leq s_{gt} \times pop_t \times p_t \equiv \overline{f}_{gt} \tag{14}$$

where $s_{gt}$ is the *observed share* of an in-metro station operating in format $g$, market $t$, and $p_t$ is the *observed ad price*.[15] A lower bound can be computed from the necessary condition (ii):

$$f_{gt} \geq \mathcal{S}_{gt}(N_t + e^g, d_t, \theta_0) \times pop_t \times \mathcal{P}_t(N_t + e^g, d_t, \theta_0) \equiv \underline{f}_{gt} \tag{15}$$

where $e^g$ is a ten-vector with zeros everywhere and the $g^{th}$ entry equal to 1. This necessary condition implies that an additional in-metro entrant into format $g$ would not be able to recover its fixed costs of operation. Notice that computing this bound requires predictions for both the counterfactual market share enjoyed by such a potential entrant, $\mathcal{S}_{gt}(\cdot)$, and for the counterfactual market ad price $\mathcal{P}_t(\cdot)$. The latter prediction requires computation of the counterfactual total market share of in-metro stations, and application of the inverse demand curve in (12).

In the event that no stations are observed in the $(t, g)$ market-format cell, one cannot compute these bounds. Clearly, there is no information that provides an upper bound on fixed costs. Moreover, we do not have an estimate of $\delta_{gt}$, the mean utility level associated with such stations, so computation of a lower bound is also infeasible.[16] As a consequence, we set $\underline{f}_{gt} = 0$, $\overline{f}_{gt} = \infty$ in this case.

For a given format $g$, we can use the cross-section of estimated intervals $[\underline{f}_{gt}, \overline{f}_{gt}]$ across markets to obtain upper and lower bounds on the Empirical Distribution Function (EDF) of format $g$'s fixed costs across markets. Denoting the total number of markets by $N_m$ (where $N_m = 163$ as discussed in Section 2), we have, for each constant $c > 0$:

$$\frac{1}{N_m}\sum_{t=1}^{N_m} I\{\overline{f}_{gt} \leq c\} \leq \frac{1}{N_m}\sum_{t=1}^{N_m} I\{f_{gt} \leq c\} \leq \frac{1}{N_m}\sum_{t=1}^{N_m} I\{\underline{f}_{gt} \leq c\} \tag{16}$$

That is, the EDF of the lower (upper) bounds on fixed costs in format $g$ is an upper (lower) bound on the EDF of these costs. If one assumes, in addition, that $f_{gt}$ are independent (over markets) draws from the true CDF of fixed costs in this format, then the EDFs of the bounds in

[15] Recall that, due to the within-format symmetry, $s_{gt}$ is computed by dividing the total listening share of in-metro stations in format $g$ by the number of such stations. Also, note the difference between the variables $s_{gt}$ and $p_t$, that are computed directly from data, and $\mathcal{S}_{gt}(\cdot)$ and $\mathcal{P}_t(\cdot)$, that are predicted by the model.

[16] One can compute the systematic portion of this utility level $x_{gt}\beta$, but, without an actual observation, no estimate is available for the unobserved taste shifter $\xi_{gt}$.

(16) converge to lower and upper bounds on this true CDF as $N_m \to \infty$. Importantly, however, we will not rely on such an IID assumption, and will not use the bounds from (16) in our analysis. We shall merely present graphs of the estimated EDFs for illustrative purposes. What we do employ in our welfare analysis are the intervals $[\underline{f}_{gt}, \overline{f}_{gt}]$ for each market-format cell.

**Bounds on fixed costs with both horizontal and vertical differentiation.** Inference on fixed costs proceeds along similar lines as in the base case in which only horizontal differentiation was allowed. The estimated threshold parameters $j'_{gt}$ allow us to classify observed stations into market-format-quality cells. The estimated mean-utility levels for each such cell allow one to compute revenues under the observed equilibrium, and under entry counterfactuals, that provide the desired upper and lower bounds on fixed costs in such cells. We need to deal with the fact that the values of $j'_{gt}$ were not assigned in some cases, as discussed in subsection 3.1.2 above. We defer discussion of this issue to Section 4.

A challenge to the estimation of bounds on fixed costs under quality differentiation concerns the computation of the market's ad price. In our base-case analysis we compute the observed ad price by dividing the market's observed total revenue by the observed total number of listeners to in-metro stations. In that analysis, the model-predicted share of listeners to in-metro stations matched the share observed in the data. This is no longer true in our vertical-differentiation model: the predicted total listenership to in-metro stations no longer matches the data, a fact rationalized by measurement error. Since upper bounds are computed from observed revenues, whereas lower bounds are computed from counterfactual (predicted) revenues, this issue can create an artificial wedge between the two. To overcome this issue, we compute the "observed" ad price by dividing total revenue by the number of listeners to in-metro stations that is predicted by the model given the observed market structure, rather than by the number of listeners observed in the data. If the observed listening data is indeed subject to measurement error, this approach is appropriate, and allows for a consistent analysis.

**Bounds on the empirical distribution of fixed costs: descriptive evidence.** Beginning with the base case where only horizontal differentiation is allowed, for illustrative purposes, we provide graphs of bounds on the EDF (or, under an IID assumption, CDF) functions of fixed costs in the various formats in Figures 1-2. The bounds are tight except for formats where selection is an issue: Religious, Urban, and Spanish. This happens since empty market-format cells reveal no information on the relevant fixed cost. The CDF graphs for the leading formats are quite steep. In the Mainstream format, 21%-31% of stations have costs lower than \$1M, 54%-64% have costs lower than \$2M , and 81%-84% have costs lower than \$5M .

Comparing the graphs for the leading formats, it does not appear that there are striking differences in the distribution of costs among such formats. As discussed below, there are some reasons why such distributions could differ across formats, which is why we do not want to impose that they are identical. In any event, what we end up using in our welfare analysis is not format-specific distributions but the market-format-specific bounds on fixed costs. As a consequence, making (or not making) assumptions on variation of fixed costs across formats does not affect our welfare analysis.

Considering next the case where vertical differentiation is allowed in the Mainstream and News/Talk formats, Figure 3 shows bounds on the EDFs of fixed costs in those formats, for high-quality stations and for low-quality stations separately. The costs of operating a high-quality station appear to be higher, in a distributional sense. This is not surprising: given that our estimate of $\gamma^q$ is positive, high-quality stations are predicted to enjoy higher mean utilities, and so higher revenues, than low quality stations. This implies that both the lower bound and the upper bound on fixed costs should be higher for high-quality stations.

**Discussion: sources of fixed costs.** Our model allows for different distributions of fixed costs for different formats. It is worth discussing what might drive such heterogeneity. Our approach assumes away marginal costs, as the non-rival nature of Radio signals makes it seem inappropriate to model the cost of serving a marginal listener. All the costs of operating a Radio station, therefore, are considered here to be fixed. These include the cost of equipment, employee salary, licensing fees and royalties paid for content.

While equipment costs need not, a-priori, diverge across formats, the cost of the content provided can vary substantially. A station that operates in a niche segment such as Jazz may need to physically possess thousands of records or music CDs, while a "big hits" station need not incur such costs.[17] Another example is that some formats (most notably, News/Talk) may hire Radio "personalities" while other formats would spend mostly on music content. In light of the above, we allow the distributions of fixed costs to diverge across formats, leaving it to the data to inform us about such potential divergence.

## 6 Socially-optimal market structures and welfare analysis

In this section, we use the estimated model to calculate, in each market, the market structure that would have been chosen by a social planner. The planner takes into account the surplus available to Radio stations and advertisers, on the one hand, and the fixed costs of operation, on the other hand. Similarly as in BW99 we cannot take into account listeners' surplus, since listeners do not pay for tuning in to a Radio broadcast. As a consequence, it is not possible to evaluate their willingness to pay for Radio broadcasting, or their surplus. As explained below, however, we are able to gain some perspective on the issue of listeners' surplus. While it is difficult to make strong statements on this issue, the analysis provides some suggestive evidence that the losses to listeners may not be so large as to outweigh the gains to market participants from station elimination.

[17] See, for example http://www.ehow.com/how_2316008_calculate-startup-costs-Radio-station.html.

The next two subsections proceed by discussing separately the optimal market structures in the base case, where only horizontal station differentiation is considered, and in the case where discrete, unobserved quality differentiation is allowed.

### 6.1 Base analysis: horizontal station differentiation

Under the base case, a market structure is a vector $N$, describing the numbers of in-metro stations in each of the formats. Let $N_f$ denote the dimension of this vector. In our case, it is equal to ten since we have ten format groups. Conditional on the market structure, welfare is given by:

$$W(N) = pop \int_0^{S_1(N)} p(x)dx - \sum_{j=1}^{N_f} N_j \times f_j \tag{17}$$

where $pop$ is market population, $S_1(N)$ is the total listening share to in-metro stations, $N_j$ is the $j^{th}$ component of $N$, and $f_j$ is the fixed cost associated with operating an in-metro station in format $j$ in the given market.[18] Advertisers' inverse demand function is given by $p(\cdot)$. Searching for an optimal market structure involves solving a $N_f$-dimensional discrete (in the sense that numbers of stations must be integers) problem in each market. The algorithm which performs this task is described in Appendix A. Importantly, if a given market-format cell has no observed stations in the observed sample, we fix the number of stations in that market-format to zero when computing the optimal market structure. Thus, we do not capture under-provision situations where the market outcome leads to zero stations in the market-format cell, whereas the social planner would have chosen a positive number of such stations. We can, however, capture under-provision situations where, say, one station is observed, and the social planner would prefer to have two.

The analysis is complicated by the fact that we do not have a point estimate of the fixed costs $f_{gt}$ for stations in market $t$, format $g$, but rather an estimated interval $[\underline{f}_{gt}, \overline{f}_{gt}]$. In our analysis, we simply set the fixed cost at the middle of this estimated interval. These intervals are typically rather small, suggesting that the bias resulting from this approach should be minimal. To strengthen this claim, we provide below a robustness check that uses the estimated bounds themselves, rather than the middle of the estimated interval.

The results of applying this "middle-of-interval" approach are given in Table 7. The table averages over the numbers of stations in each format in all 163 markets. Excessive entry, on average across markets, is apparent in all ten formats. In total, the average market has 19.58 in-metro stations, whereas the optimal number of such stations is 50% lower: 9.79. The discrepancy between the observed and optimal numbers seems to be split quite evenly among the various formats. In most formats, an average reduction of about 50%-60% in the number of in-metro

[18] Once again, it is understood that market shares also depend on the presence of out-metro stations.

stations is optimal. The least amount of excessive entry occurs in the CHR and Oldies formats, where the average optimal reductions are 20% and 14%, respectively. Notice that these formats tend to have very few stations in the typical observed market, so the scope for excessive entry is *a-priori* rather limited.

As a robustness check for the validity of the "middle-of-the-interval" approach, we consider an alternative strategy: fixing a format $g$, we set fixed costs in that format to their lower bound, $\underline{f}_{gt}$, and set fixed costs in all other formats $m \neq g$ to their upper bounds, $\overline{f}_{mt}$. Then, we compute the optimal number of in-metro stations in format $g$. This quantity can be interpreted as an upper bound on the true optimal number. Analogously, a lower bound on this optimal number can be achieved by setting fixed costs in format $g$ to their upper bound, and fixed costs in all other formats to their lower bounds.[19]

The results of this approach are given in Table 8. The mean optimal total number of in-metro stations in a market is bounded by 9.2 from below, and by 10.75 from above, implying an excessive entry rate which is bounded between 47% and 55%, compared to the rate of 50% found using the "mid-interval" approach. A similar pattern is observed at the level of the individual format: the results obtained using the "mid-interval" approach tend to lie between the bounds on the optimal numbers. For example, as can be seen in Table 8 for the Mainstream format, the mid-interval approach yields a mean optimal number of 1.38 in-metro stations, which lies between the bounds 1.29 and 1.60. Moreover, in 81% of the format-market cells that have at least one observed in-metro station, the upper and lower bounds on the optimal numbers of stations coincide. All these facts are quite reassuring that our findings are not sensitive to the exact manner in which we use the estimated fixed cost bounds.

The averages reported in Tables 7 and 8 suggest substantial excessive entry. It is worthwhile to explore beyond average numbers and look at some particular examples that compare observed and optimal station allocations (using the "mid-interval" approach). Interestingly, only two markets (out of the 163 markets analyzed) display efficiency of the free-entry equilibrium, in the sense that the optimal market structure vector coincides with the one observed in the data: Bloomington, IL, and Lancaster, PA. Both are small markets where the number of observed stations is small. Specifically, these markets never have more than one in-metro station in a given format, and so the scope for potential excessive entry is small to begin with.[20]

Also important is that insufficient entry is hardly ever detected: in the entire sample, there are only six market-format pairs in which the optimal number of stations exceeds the observed

[19] While this is an intuitive approach, it is difficult to formally prove that it generates bounds on the true optimal market structures.

[20] To re-iterate, this finding implies that, in formats where at least one station is observed, there is no under-provision of stations (e.g., a social planner would not like to have two Rock stations instead of one). However, as explained above, we do not look into the possibility that a format with zero observed in-metro stations should (according to the social planner) have a positive number of stations. As a consequence, we cannot rule out the possibility that these two markets suffer from under-provision of stations in these "empty" formats.

number. Three of these cases involve the News/Talk format. In the Radio market of Portsmouth-Dover-Rochester (New Hampshire), the social planner would like to eliminate one Rock station and one Country station—and add one Mainstream station and one News/Talk station instead. Such re-allocation is very a-typical: in almost all markets, the social planner is interested in (weakly) removing stations in all formats, rather than removing stations from some formats while adding stations to other formats.

Table 9 reports additional information regarding the discrepancy of the observed and optimal market structures. The results indicate that the welfare loss associated with free entry is about \$1.8 billion, or 13%. Under optimal market structures, which imply fewer in-metro stations, the mean (across markets) total listenership to such stations drops substantially from 11.1% to 8.15%. The cross-market average ad price under the optimal market structures is 662.54\$, compared to 570.48\$ in the observed, free-entry equilibrium.

**Listener welfare.** The analysis thus far has ignored the positive externalities conferred upon listeners from broadcasting. Simply put, the social planner's elimination of stations reduces total listening, and hence listener's utility. Measuring the lost listener surplus is difficult on account of the radio signal being non-rival and non-excludable. At the same time, observing some benchmark figures can provide some idea about the lost listener surplus.

The first exercise we perform works as follows: the station elimination prescribed by the social planner discussed above leads to a reduction in the total listening share to in-metro stations. Multiplying the lost shares by the relevant market populations, and summing over all 163 markets, we obtain that a total of 6.02 million listeners are "lost" to the Radio industry.[21] To offset the welfare gains to advertisers and stations, totalling \$1.8 billion, the average "lost" listener would need to be willing to pay at least \$299 for a year's worth of radio listenership. While learning about listeners' willingness to pay for a free product is very difficult, we may derive a useful benchmark from subscription fees to Satellite radio.

A monthly subscription to XM Sirius's most basic satellite radio services cost \$14.49 in August 2013, translating into an annual subscription cost of \$173.8.[22] We view this amount as an upper bound on the true willingness to pay for the terrestrial radio broadcasting that we analyze in this paper, given that satellite radio is a premium product. If that is the case, we may conclude that the willingness to pay is much lower than \$299. While this is clearly a very rough calculation, it does suggest that the lost listener welfare may not be large enough to offset the combined gains of the market participants (stations and advertisers).

[21] A subtle issue is that eliminating in-metro stations in one market also eliminates them as out-metro stations in another market, and our count of lost listeners does not take that into account. Adjusting the analysis to account for this issue would be quite demanding as it requires the mapping of each in-metro station in each market to all other markets in which it is an out-metro station. Since our goal is to provide a back-of-the-envelope calculation only, and since listenership to out-metro stations is systematically lower than listenership to in-metro stations to begin with, we ignore this cross-market externality in our analysis.

[22] http://www.sirius.com/ourmostpopularpackages-sirius.

As an alternative approach, we consider an exercise that involves listener's expected utility, as defined by the nested logit formulae. The benefit of this approach is that expected utility is calculated from an "ex-ante" perspective (i.e. prior to the realization of the listener-specific utility shocks), and takes into account some gains from variety which would be clearly reduced if the social planner was to reduce the number of active stations in the market. Summing over all 163 markets, we find that the total loss of expected utility of all listeners in all markets is given by 6.56 million "utility units."[23] If this lost listeners' utility is to exactly offset the $1.8 billion gains to the market participants (again, stations and advertisers), each utility unit must, therefore, be worth $274.[24]

With this conversion rate at hand, we can try to evaluate its implications for listeners' willingness to pay. For concreteness, let us focus on the New York City Radio market. Beginning with the observed set of stations, let us contemplate an elimination of all four stations in the Rock format. We can calculate the impact of this elimination on the expected utility of the representative member of NYC's population (twelve years of age and above), and transform it to monetary terms using the conversion rate computed above. Each such person would incur a loss of 0.013 utility units, or, $3.62. A similar calculation would show that the monetary surplus lost as a consequence of eliminating all the market's stations would be $44.12.

What we learn from this exercise is that, if listeners' willingness-to-pay for Radio is high enough to offset the welfare gains from station elimination, it would have to be true that each person living in NYC, prior to drawing her listener-specific utility shocks, would have to be willing to pay about $44 per year to be able to access the Radio market. Given that the share of Radio listenership in NYC is lower than 15%, this may seem like a large number. While it is hard to draw strong conclusions from this exercise, it provides some suggestive evidence that listener's willingness to pay may not be high enough to offset the welfare gains from the station elimination prescribed by our social planner (who cares only about the welfare of market participants, and ignores externalities on listeners).

Another way to gain perspective of the issue is to use the conversion rate computed above to compute the expected surplus loss to listeners if one were to remove a single Rock station from the NYC market. This loss amounts to $5.3 million, which falls short of the combined gains to advertisers and stations, amounting to $6.4 million. In other words, even if listeners' willingness to pay is high enough to offset the gains to market participants from the massive stations elimination prescribed by our social planner, it would still be true that removing one Rock station would be optimal, i.e., the lost listener surplus from this modest station elimination would not be large enough to offset the gains.

[23]Where expected utility is given by $\log\left(\sum_g exp(I_g)\right)$ with $I_g$ being nest $g$'s "inclusive value."

[24]The same caveat about ignored cross-market externalities involving out-metro stations, discussed with respect to the previous analysis above, continues to apply to this analysis as well.

To sum, we view the above analysis as providing some perspective on the issue of the negative externalities on listeners' welfare that would result from station elimination. Overall, we view this evidence as consistent with there being at least some degree of excessive entry, even if one would take into account the externalities on listeners. Ultimately, however, it is hard to draw strong conclusions on the issue of listeners' surplus, and in the remainder of the paper, we continue to focus on a welfare analysis that takes into account the surplus of market participants: stations and advertisers.

### 6.2 Optimal market structures with both horizontal and vertical differentiation

We next compute the optimal market structures in the case that allows, in additional to horizontal differentiation, vertical differentiation in the Mainstream and News/Talk formats. The algorithm that computes optimal market structures is employed once again, this time with $N$ being a 12-vector: eight elements of this vector describe the numbers of stations in each of the eight formats where quality differentiation is not allowed, and four additional elements describe the numbers of high quality and low quality stations in the Mainstream and News/Talk formats.

An issue that must be tackled is that quality was not determined in some format-quality cells, as discussed in subsection 3.1.2 above. In those cases, all we know is that all stations in the market-format pair offer identical quality - but we do not know which quality level it is. The assignment of this quality affects the analysis of optimal market structures via two channels. First, it affects stations' revenues under both the observed equilibrium, and under entry counterfactuals. As a consequence, this quality assignment affects the estimated fixed costs bounds.[25] In addition, since the quality assignment affects revenues and advertisers' surplus, it affects the computation of the optimal market structure conditional on fixed costs.

We address this issue using the following strategy: in markets where quality was undetermined (in Mainstream, News/Talk, or both) we proceed by estimating fixed costs bounds and computing market structures under each *possible* quality assignment. For example, in a market where quality was unassigned in the Mainstream format, we consider two possible market structures: one in which all observed Mainstream stations offer low quality, and one where they all offer high quality. In each such scenario, we can compute bounds on fixed costs, and, using the "mid-interval" approach as above, compute the optimal market structure vector. We then compute upper (respectively, lower) bounds on the optimal number of stations in each component by taking the element-by-element maximum (minimum) over these two vectors. We address similarly markets where quality was undetermined in the News/Talk format (again considering two possible scenarios and computing two optimal vectors), and markets where quality was undetermined in

[25] Interestingly, since the fixed effects $\psi$ adjust to perfectly offset the effect of shifting *all* stations in the relevant format from one quality level to another, the market shares and revenues of stations in other formats are actually not affected. Only fixed costs in the particular format in which quality was unassigned, therefore, can be affected by the quality assignment.

both Mainstream and News/Talk (leading to four possible scenarios and to the computation of four optimal vectors).

Results from this analysis are offered in Table 10. Panel A displays findings for the eight formats in which quality differentiation was not allowed. The left column presents the mean (over markets) number of observed in-metro stations in such formats, while the middle column presents the mean optimal number of such stations. The optimal number of stations in these formats is unaffected by the issue of whether we identify the quality level of stations in the Mainstream and News/talk formats. As a consequence, we point-identify the socially-optimal mean number of stations in all of these eight formats. The right column reports the elimination rates: very similarly as in the base case analysis, the social planner would choose to eliminate about 50%-60% of in-metro stations in all formats, with the exception of the very small formats CHR and Oldies where elimination rates of 20.2% and 16.2% are optimal.

Panel B reports findings for the two formats where we allow for quality differentiation. In markets where the quality of observed stations was not determined, we get bounds on both the observed and the optimal numbers of stations in these two formats. The table reports the means (across markets) of the upper and lower bounds on these numbers of stations. In the News/Talk format, the average number of observed low-quality stations ranges between 1.83 and 2.02. The average optimal number ranges between 0.79 and 0.89. This implies that the social planner would like to eliminate, on average, 51.3%-61.2% of the low-quality News/Talk stations that are observed in equilibrium. A similar picture emerges with high-quality stations in this format: the mean observed number of such stations is bounded between 1.06 and 1.25, while the mean optimal number is bounded between 0.40 and 0.51, implying an optimal elimination rate of 51.7%-67.6%. Two points emerge from these numbers: first, the optimal elimination rate is rather similar in both quality levels. Second, this is a similar elimination rate—50 to 60 percent— to that found in the base analysis where quality differentiation was not allowed.

In the Mainstream format, as discussed above, there is a higher incidence of cases where the quality level of observed stations was undetermined. As a consequence, the bounds on the optimal reduction in the numbers of stations are wider: 44.1%-81% in the low quality case, and 38.6%-74.2% for high quality stations. Just the same, those findings are in line with the overall elimination rate of 50 to 60 percent which holds quite consistently throughout our analysis.

**How often is quality misallocated in equilibrium?** Having computed the optimal market structure, we next wish to pay particular attention to the optimality of quality allocations in the free-entry equilibrium. While the findings above suggest that, *on average*, the social planner would like to eliminate high quality and low quality stations at similar rates, it is of interest to ask whether—and how often— does the optimal quality level of stations differ from the one observed in equilibrium.

We address this issue by asking the following question: beginning with the market structure observed in equilibrium, how often can welfare be improved by converting an observed low-quality station into a high-quality one? And, vice versa, how often can welfare be improved by converting an observed high-quality station into a low-quality one? In contrast to the analysis offered above where the optimal market structure was computed, here we consider only "local" changes to the observed market structure, holding the total number of stations fixed.

In practice, let us consider market $t$ and format $g$, where $g$ is one of the two formats in which we allow quality differentiation. Let $f_{gt\ell}, f_{gth}$ correspond to the true fixed costs associated with operating a low quality station and a high quality station in this market-format cell, respectively. Suppose that this format has low-quality stations present in the observed equilibrium. We ask whether converting one such station into high-quality operation would increase social benefits (the sum of stations' revenue and advertisers' surplus) by more than the difference $\overline{f}_{gth} - \underline{f}_{gt\ell}$, where overlines and underlines correspond, as above, to upper and lower bounds, respectively. If this condition is met, underprovision of quality prevails in this case, in a local sense. Analogously, if high-quality stations are observed, we shall ask whether converting one of them to low quality would decrease social benefits by an amount smaller than the difference $\underline{f}_{gth} - \overline{f}_{gt\ell}$.[26]

A challenge arises in determining the welfare consequences of converting a low-quality station into a high-quality one, if no high quality stations are observed in the data: no estimate of $\overline{f}_{gth}$ is available. This happens since upper bounds on fixed costs are generated from the observed revenue of stations in the relevant data cell. Importantly, however, since a low-quality station was observed, an estimate for $\psi_{gt}$, the market-format fixed effect, is available, and so it is possible to compute the mean-utility level of a hypothetical high-quality station as $\psi_{gt} + \gamma^h + \gamma^q$. With this mean-utility level at hand, it is possible to compute the lower bound $\underline{f}_{gth}$ from the hypothetical revenue of such a hypothetical entrant, conditional on the observed market structure.

Our approach in such cases is to set the value of the unknown $\overline{f}_{gth}$ equal to $\underline{f}_{gth} + \mu^h$, where $\mu^h$ is the maximum difference $\overline{f}_{gth} - \underline{f}_{gth}$ taken over all market-$t$, format-$g$ pairs in which high quality stations were observed (so that the computation of both $\overline{f}_{gth}$ and $\underline{f}_{gth}$ is possible). Similarly, when considering the conversion of a high quality station into a low quality one in a market-format cell where no low quality stations are observed, we use as our estimate of $\overline{f}_{gt\ell}$ the quantity $\underline{f}_{gt\ell} + \mu^\ell$ where $\mu^\ell$ is the maximum difference $\overline{f}_{gt\ell} - \underline{f}_{gt\ell}$ taken over all market-$t$, format-$g$ pairs with observed low-quality stations.

The results of this exercise are quite telling: out of 90 markets with observed high-quality Mainstream stations, in 72 cases welfare can be unambiguously improved by converting one of those stations to low quality operation.[27] In other words, overprovision of quality in the local sense occurs at a rate of 80%. An even higher rate, 94.9%, applies to the News/Talk format (74

[26] Advertisers' surplus unambiguously increases when higher quality is offered, since that generates higher listenership and lower ad prices. The effect on stations' total revenue, in contrast, is ambiguous.

[27] Markets in which quality was undetermined in either the Mainstream or News/Talk formats where excluded from this exercise.

out of 78 markets). On the other hand, there are no cases where a market has observed low-quality stations—in either format—and converting one of them to high quality would unambiguously improve welfare. Our analysis of local changes to quality offerings, therefore, reveals a highly-asymmetric pattern: over-provision of quality appears to be widespread, whereas under-provision is not encountered.

## 7 Concluding remarks

The goal of this paper is to introduce horizontal and vertical differentiation into the analysis of excessive entry in local Radio markets. Introducing such systematic heterogeneity creates three main challenges: first, we deal with the non-uniqueness of equilibrium and the resulting partial identification of fixed costs. Second, we deal with estimating a model that allows for quality as an unobserved station characteristic. Finally, we deal with the computational challenge of computing non-scalar optimal market structures.

Notwithstanding these challenges, the results indicate that allowing for discrete station differentiation is important. It appears to soften the excessive entry finding to some extent, placing it at 50%-60%, compared to 74% in BW99, where such differentiation was not allowed. The optimal elimination rates are quite robust across different specifications of the model. The results also demonstrate that the optimal elimination rate is quite uniform across horizontal formats and vertical quality levels. Considering *local* changes to the observed equilibria, there is a very high incidence of quality overprovision: welfare can be improved by converting a high quality station into a low quality one.

To sum, extending traditional entry models to allow for horizontal and vertical differentiation can create a rich framework in which various questions concerning the divergence of free-entry equilibria and optimal market structures can be addressed. Such an agenda is particularly attractive given that theoretical analyses of such questions often provide ambiguous predictions that depend on specific parameter values. This motivates empirical work that attempts to estimate such parameters (e.g., the magnitude of fixed costs).

## A Computing optimal market structures

Define $\Delta W^j(N)$ as the change in welfare resulting from adding an in-metro station to format $j$, $1 \leq j \leq N_f$, compared with a benchmark market structure $N$:

$$\Delta W^j(N) = pop \times \int_{S_1(N)}^{S_1(N+e_j)} p(x)dx - f_j$$

Let $f$ be a known $N_f$-vector of fixed costs for the market's format categories.[28] The following algorithm calculates the optimal market structure:

1. Let $\underline{N}_\ell$ be a lower bound on the optimal number of in-metro stations in format $\ell$ (initially set $\underline{N}_\ell = 0 \ \forall \ell$). Fix format $j$, $1 \leq j \leq N_f$. We obtain an integer, $\overline{N}_j$, interpreted as an upper bound on the optimal number of in-metro stations in format $j$, as follows: we set $\overline{N}_j = 0$ if the following condition is met:

$$\Delta W^j(\underline{N}_1, \underline{N}_2, ..., \underline{N}_{(j-1)}, 0, \underline{N}_{(j+1)}, ..., \underline{N}_{(N_f)}) < 0 \tag{18}$$

   Otherwise, we set $\overline{N}_j = \tilde{N}_j$ where $\tilde{N}_j$ is the smallest positive integer that satisfies:[29]

$$\Delta W^j(\underline{N}_1, \underline{N}_2, ..., \underline{N}_{(j-1)}, \tilde{N}_j - 1, \underline{N}_{(j+1)}, ..., \underline{N}_{(N_f)}) \geq 0 \tag{19}$$

$$\Delta W^j(\underline{N}_1, \underline{N}_2, ..., \underline{N}_{(j-1)}, \tilde{N}_j, \underline{N}_{(j+1)}, ..., \underline{N}_{(N_f)}) < 0 \tag{20}$$

   We Repeat the above for $j = 1, ..., N_f$ to obtain a vector of upper bounds, $\overline{N} = (\overline{N}_1, ..., \overline{N}_{(N_f)})$

2. Again fix a format $j$. We compute a new lower bound $\underline{N}_j$ as follows: we set $\underline{N}_j = 0$ if the following holds:

$$\Delta W^j(\overline{N}_1, \overline{N}_2, ..., \overline{N}_{(j-1)}, 0, \overline{N}_{(j+1)}, ..., \overline{N}_{(N_f)}) < 0 \tag{21}$$

   Otherwise, we set $\overline{N}_j = \tilde{N}_j$ where $\tilde{N}_j$ is the smallest positive integer that satisfies:

$$\Delta W^j(\overline{N}_1, \overline{N}_2, ..., \overline{N}_{(j-1)}, \hat{N}_j - 1, \overline{N}_{(j+1)}, ..., \overline{N}_{(N_f)}) \geq 0 \tag{22}$$

$$\Delta W^j(\overline{N}_1, \overline{N}_2, ..., \overline{N}_{(j-1)}, \hat{N}_j, \overline{N}_{(j+1)}, ..., \overline{N}_{(N_f)}) < 0 \tag{23}$$

   We Repeat the above for $j = 1, ..., N_f$ to obtain a vector of lower bounds, $\underline{N} = (\underline{N}_1, ..., \underline{N}_{(N_f)})$

[28] Recall that, in practice, we have estimated only *bounds* on these costs. As explained in the text, one approach we took was to use the middle of the estimated interval.

[29] It is easy to prove that $\tilde{N}_j$ exists, and is unique.

3. Go back to step 1, unless the stopping rule in step 4 below is satisfied.

4. Stopping rule: Stop the process either when $\overline{N} = \underline{N}$ (convergence to the optimal structure), or after 20 iterations of steps 1 and 2. In the latter scenario, enumerate all possible $N_f$-vectors $N$ such that $\underline{N} \leq N \leq \overline{N}$ (this is an inequality in vector sense), calculate welfare in each of them, and set the optimal vector $N^*$ to the vector yielding the highest welfare.

In practical implementation, convergence to the optimal market structure was achieved in 144 of the 163 markets, typically very quickly within 2-4 iterations. In the remaining cases, enumeration was used (as explained in Step 4 above) to determine the optimal market structure.

Theorem 1 establishes that this algorithm produces the optimal market structure for a given market, if fixed costs are known. As discussed in the text, only bounds on fixed costs are available in practice, and we take a couple of approaches to deal with this challenge.[30]

**Theorem 1.** *Assume that the market has a unique optimal structure and that fixed costs are known.*[31] *The algorithm above recovers the optimal vector for the relevant market.*

# B Robustness: within-format symmetry and selection

In this section we investigate the robustness of the listening equation estimation in the base case where only horizontal differentiation is allowed. As pointed out in section 3.1 above, we focus on two issues: the symmetry assumption, and the potential selection bias.

**The symmetry assumption**. Our base-case analysis assumes that stations within a market-format cell are symmetric, i.e., they have the same mean utility level.[32] We investigate robustness by estimating a listening equation which does not impose this restriction. Dropping this assumption allows one to control for station-level variables such as an FM dummy variable, transmission power (in 100 MHz units) and Antenna height (in thousand feet above average terrain). A comparison of the symmetric vs. non-symmetric specifications is provided in Table 11.

The left-hand column ("symmetric") replicates the results of the baseline specification reported in Table 4, while the right-hand column provides results for the non-symmetric specification. Relaxing the symmetry assumption causes the key parameter $\sigma$ to increase slightly, from about 0.52 to about 0.61. Also note that the regional and demographic effects appear very robust to the symmetry assumption, although the "home" and some of the format effects do change. In total,

[30] A proof of this theorem is available from the authors upon request.

[31] The market may fail to have a unique optimal structure if, for example, at some optimal solution $N^*$, we have that $\Delta W^j(N^*) = 0$, i.e., the benefit to advertisers from an additional station is exactly offset by fixed costs. In this case, $N^* + e_j$ is also optimal. We effectively assume that this is a zero-probability event.

[32] As explained above, in practice we differentiated between in-metro and out-metro stations, and assumed that all in-metro (out-metro) stations within such data cells are symmetric.

it appears that the symmetry assumption is reasonable, and, in particular, does not drive the excessive entry results: imposing this assumption actually reduces the value of $\sigma$, thus pushing the analysis away from the excessive entry finding.

**Selection**. As discussed above, three formats raise potential selection issues: "Religious," "Urban," and "Spanish". To be clear, the concern is that we may only observe an "Urban" station, say, in markets where such a format is likely to be popular. If this likelihood is affected by the unobserved $\xi_{gt}$, the format-market taste error, estimation of mean-utility parameters could be biased, and, in particular, the estimate of the coefficient on the "Urban" dummy variable may be expected to be biased upward.

To address this concern, we must look into the underlying selection mechanism that determines whether a metro would have an "Urban" (or "Spanish", or "Religious") station. Both observed (by the econometrician) factors, such as the size of the metro's Black population, and unobserved factors, such as the popularity of certain musical styles in the metro, can potentially be important determinants of whether an "Urban" station would be observed. While selection on observables would not cause a bias, selection on unobserved variables is a potential problem.

As a starting point, we estimate a probit model which relates the probability of observing the format to market characteristics. The results are presented in Table 12. The size of the metro's Black population significantly increases the probability of observing an Urban-formatted station, and the size of the Hispanic population has a similar effect on the probability of observing a Spanish station. Total population seems to have no explanatory power (for the Urban format case) or even a negative effect (for the Spanish format). Location of the metro in the South region has a positive and significant effect on the probability of observing both Urban and Spanish stations. The probability of observing a Religious-formatted station is increasing in the size of the Black population, but is not significantly affected by other characteristics. In particular, location in the "South" region has a positive, but insignificant, effect on the probability of observing a Religious station.[33]

A non-parametric investigation of the relationship between Black (Hispanic) population and the likelihood of observing an Urban (Spanish) station is available in Figure 4 (and 5). Figure 4 plots a dummy variable that takes the value 1 if an Urban station (either in-metro or out-metro) is broadcasting to the metro, and zero otherwise, against the metro's Black population. Figure 5 does the same for the Spanish format, and Hispanic population.[34]

Figure 4 shows that, when the Black population is small, the metro may or may not have an Urban station. On the other hand, once the size of that population crosses a certain threshold,

[33] Since a Religious station is observed in almost 80% of the markets, it is difficult to estimate the probit parameters with precision.

[34] In both cases, NYC is excluded from the graph, as it has large Black and Hispanic populations (4.2 million in the case of Black population, 3.7 Million in the Hispanic case), and so excluding it allows for a clearer plot. In Figure 5, LA is excluded on similar grounds.

the metro *always* has an Urban station. This threshold can be characterized by the largest Black population in a metro that does not have an Urban station, and this happens in the city of Las Vegas, that has a Black population of about 110,000 persons. However, Las Vegas may be somewhat of an outlier, and the "true" threshold may be lower.[35]

A possible conclusion is that, if selection on unobservables occurs in the context of the Urban format, it is probably concentrated in those markets that have a small Black population. Figure 5 reveals similar patterns for the relationship between Hispanic population and the existence of a Spanish station, and the "threshold" population, of 129,000, is observed in Seattle-Tacoma.

The probit models of Table 12, as well as Figure 4 and 5, imply that the probability of observing an Urban (Spanish) station appears to be strongly driven by observables, i.e., the size of the main target population in the metro. For the Religious format, it is harder to locate a demographic "smoking gun" that would explain the probability of observing stations in this format, although Black population again emerges as having explanatory power.

While the evidence above is encouraging, it does not rule out selection on unobservables, and the resulting potential for selection bias. To further address this possibility, we perform a robustness check, motivated by an "Identification at infinity" approach.[36] The idea of this approach is to restrict attention to those markets where the probability of observing, say, an Urban station, as predicted by the probit specification in Table 12, is higher than, say, 99%. In this group of markets, there should be virtually no selection problem, since only a huge negative taste shock $\xi$ could prevent an Urban station from broadcasting to this metro. As a consequence, estimating the listening model using only observations from this restricted subsample of markets should yield estimates that are robust to selection bias.

We, therefore, compare the estimates of the listening function obtained using the full sample, with those obtained from subsamples that include only those markets in which the probability of observing an Urban, Spanish, or Religious station is higher than 99%. The results are presented in Table 13 below. Note the estimates which appear in bold text: these are the estimates that are most likely to be biased by selection, i.e., those pertaining to the dummy variables for "Urban," "Spanish," and "Religious," as well as relevant interactions of these dummies with demographic variables. If selection bias is important, these estimated coefficients would be lower when using the restricted subsamples compared with the results obtained using the full sample.

Rather than offering a formal test, we simply examine the relevant coefficients in Table 13, and ask whether these results are consistent with selection bias. The emerging picture appears to be mixed; the estimated coefficient on the "Urban" dummy variable is (-0.40) for the full sample, and actually increases to a statistically insignificant estimate of (-.17) in the "selection free" subsample. The coefficient on the interaction of "Urban" with the percentage of the market's

[35]Las Vegas is the most-right dot for which the "Urban Indicator" takes the value zero in Figure 4. Second-in-line is Omaha-Council Bluffs, with a Black population of about 48,000 people, and no Urban-formatted station.

[36]See for example Heckman and Navarro (2007).

Black population is decreasing very slightly, from 0.50 in the full sample, to 0.46 in the restricted subsample. There seems to be little evidence, therefore, that estimates concerning the Urban dummy variable are upward-biased due to selection.

In the case of the "Spanish" dummy, both the coefficient on this dummy variable itself, and on its interaction with the percentage of the market's Hispanic population, appear to drop when we shift from the full sample to the restricted subsample (from (-1.16) to (-1.37) for the dummy variable itself, and from .35 to .27 for the interaction term). This is consistent with a certain degree of sample selection bias. Finally, the results for the "Religious" format do not appear consistent with selection bias.

Summing up, for both the Urban and Spanish formats, there is both parametric and non-parametric evidence that the selection is strongly driven by observed metro characteristics, for which we control. Our robustness check does not indicate selection bias concerning the Urban or Religious formats. However, some findings are consistent with selection bias in the case of the Spanish format (remembering that this format is only present in 40% of the markets).

# C A closed-form solution for the fixed effects

The multinomial likelihood function of stations' market shares (as opposed to the likelihood of within-format shares, presented in the text), can be written as:

$$logL(s,x;\beta,\sigma,\xi) = \sum_t \sum_g \sum_{j\in g} n_{jt} \times \left[\frac{\delta_{jt}}{1-\sigma} - \sigma log D_{g(j)t} - log(1+\sum_m D_{mt}^{1-\sigma})\right]$$

Also note that:

$$D_{gt} = e^{\psi_{gt}/1-\sigma} \sum_{j\in g} e^{\kappa_1 \cdot q_{jt} + \kappa_2 \cdot h_{jt}} \Rightarrow \frac{\partial D_{gt}}{\partial \psi_{gt}} = D_{gt}/(1-\sigma), \;\; logD_{gt} = \psi_{gt}/(1-\sigma) + log\big[\sum_{j\in g} e^{\kappa_1 \cdot q_{jt} + \kappa_2 \cdot h_{jt}}\big]$$

Taking the FOC of the likelihood function with respect to $\psi_{kt}$ yields:

$$\begin{aligned} 0 = \frac{\partial \log L}{\partial \psi_{kt}} &= \sum_{j\in k} n_{jt}\left[1 - \frac{D_{kt}^{1-\sigma}}{1+\sum_m D_{mt}^{1-\sigma}}\right] - \sum_{g\neq k}\sum_{j\in g} n_{jt}\left[\frac{D_{kt}^{1-\sigma}}{1+\sum_m D_{mt}^{1-\sigma}}\right] \\ &= \sum_{j\in k} n_{jt}[1-\mathbf{s}_{kt}] - \sum_g \sum_{j\in g} n_{jt}\mathbf{s}_{kt} = \sum_{j\in k} n_{jt} - \mathbf{s}_{kt} \times n_t \Rightarrow s_{kt} = \mathbf{s}_{kt} \end{aligned}$$

where the second equality utilizes the nested-logit formula for the share of nest (format) $k$, and $s_{kt}, \mathbf{s}_{kt}$ are the observed and predicted shares of listening to format $k$, respectively. The above derivations show that the optimal (i.e., likelihood-maximizing) solution for the fixed effects sets predicted and observed format shares to be equal. Taking logs on both sides of $s_{kt} = \mathbf{s}_{kt}$ yields:

$$
\begin{aligned}
log(s_{kt}) = (1-\sigma)log\big[D_{kt}\big] + log(\mathbf{s}_{0t}) \\
\Rightarrow log(s_{kt}) = \psi_{kt} + (1-\sigma)log\left[\sum_{j\in k} e^{\kappa_1\cdot q_{jt}+\kappa_2\cdot h_{jt}}\right] + log(\mathbf{s}_{0t}) \\
\Rightarrow \psi_{kt} = log(s_{kt}) - log(s_{0t}) - (1-\sigma)log\left[\sum_{j\in k} e^{\kappa_1\cdot q_{jt}+\kappa_2\cdot h_{jt}}\right]
\end{aligned}
$$

The last step replaced the predicted share choosing the outside option $\mathbf{s}_{0t}$ by its empirical counterpart $s_{0t}$. This is a valid replacement since all nests' predicted shares are matched to their empirical counterparts, including the nest which only element is the outside option.

# D Figures

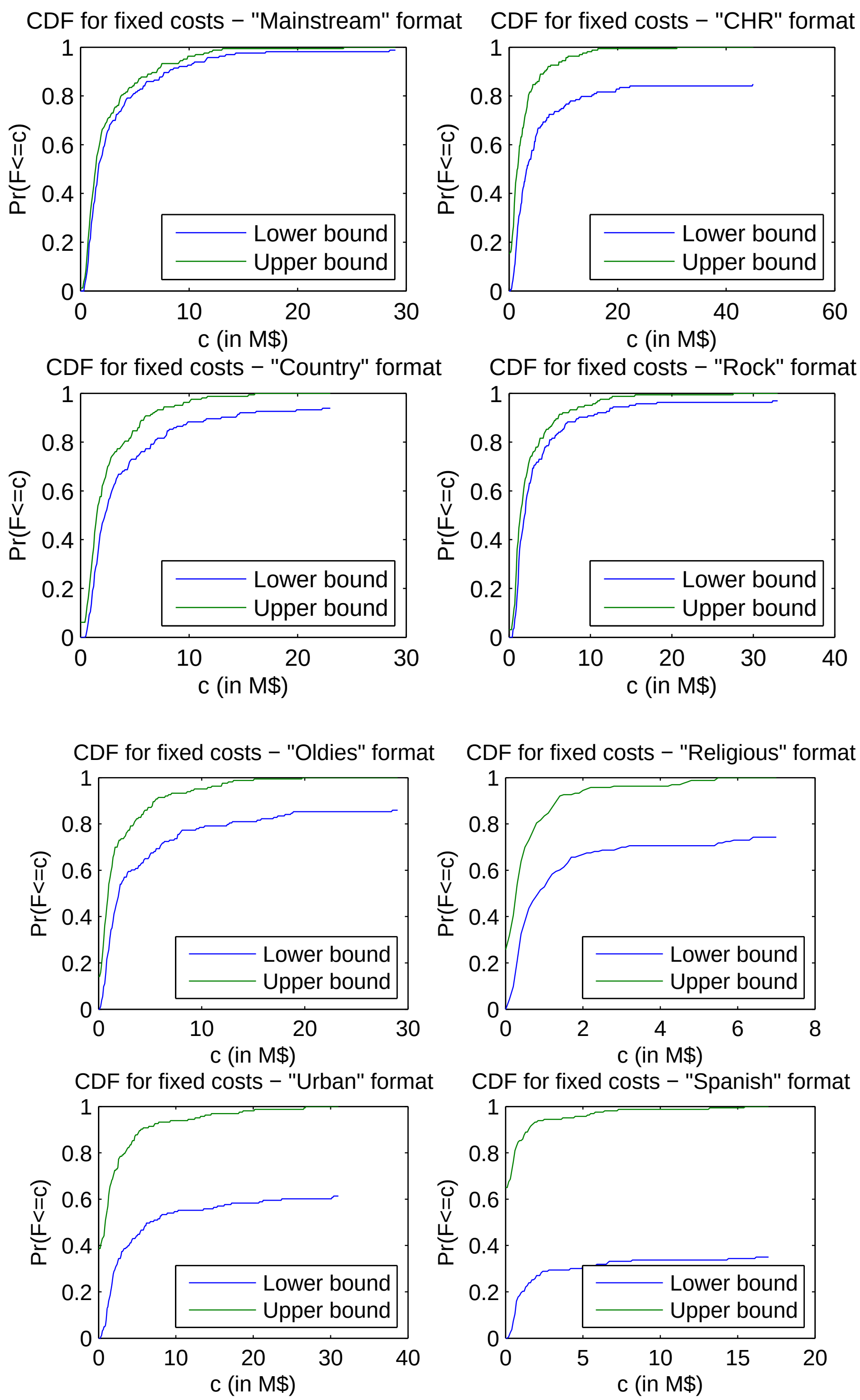


Figure 1: Estimated bounds on the CDF of fixed costs, horizontal differentiation only, formats 1-8

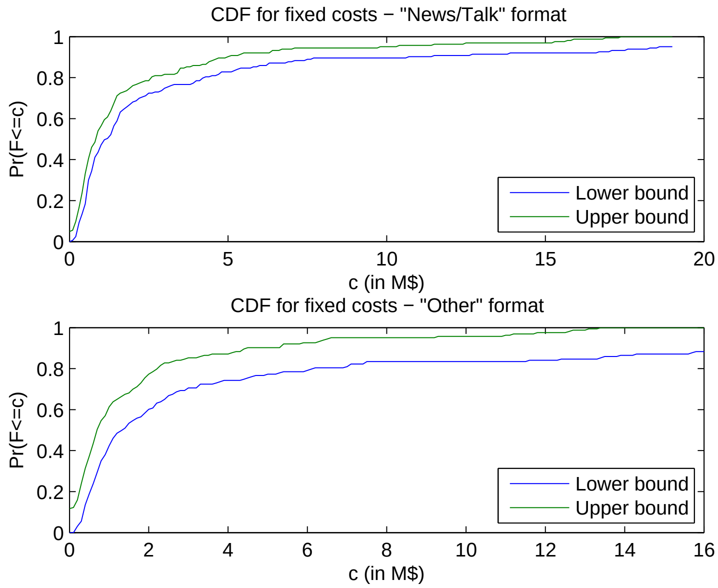


Figure 2: Estimated bounds on the CDF of fixed costs, horizontal differentiation only, formats 9-10

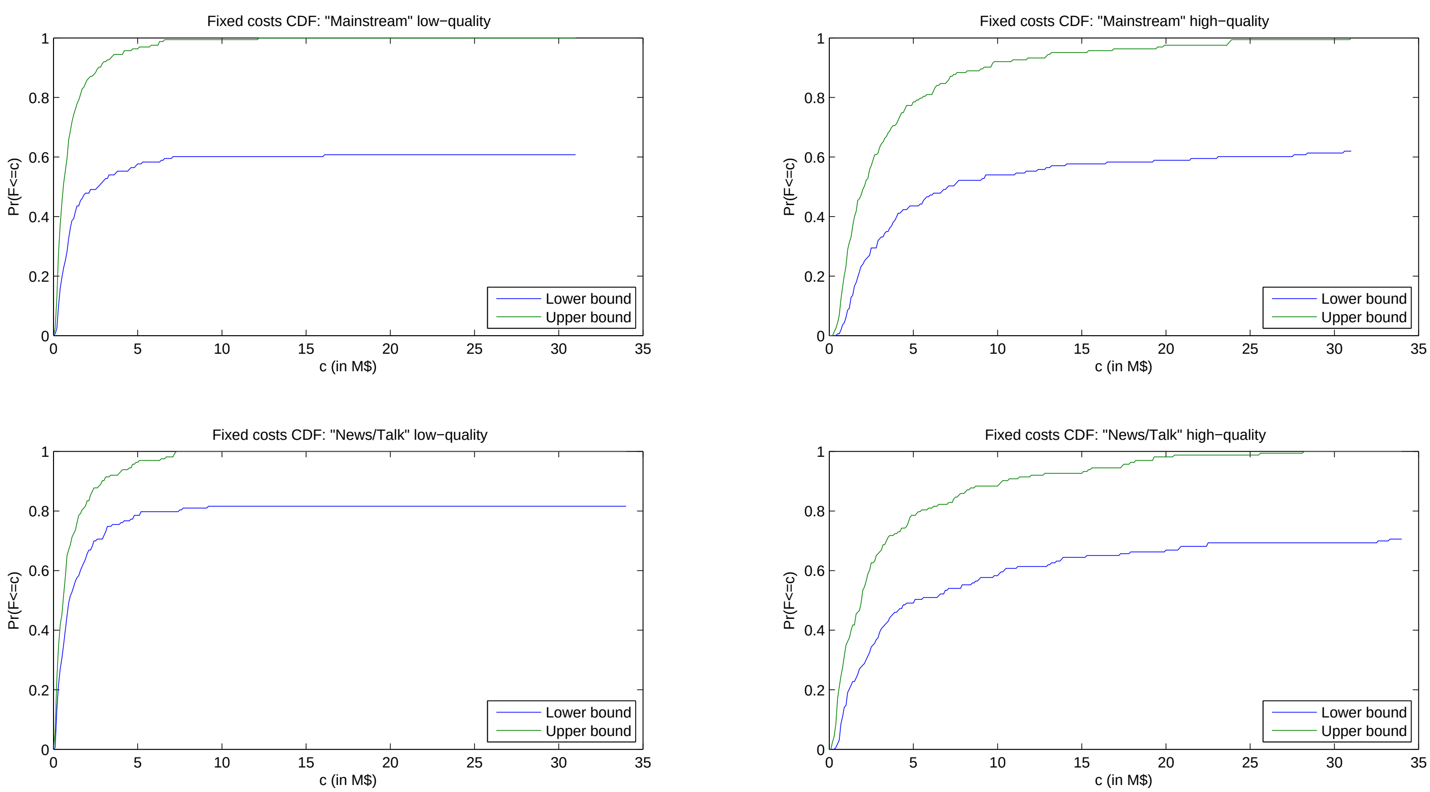


Figure 3: Estimated bounds on the CDF of fixed costs, horizontal and vertical differentiation

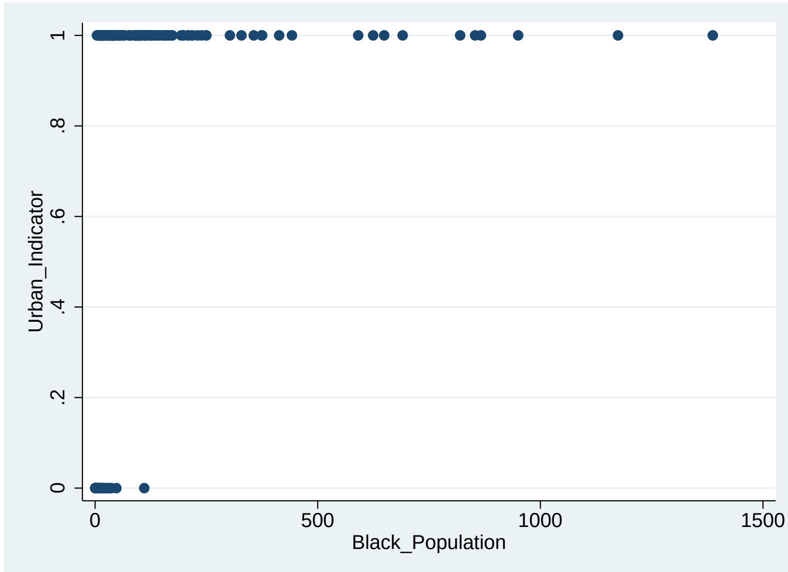


Figure 4: Presence of Urban Station Plotted against Black Metro Population, in 1000s (NYC Excluded)

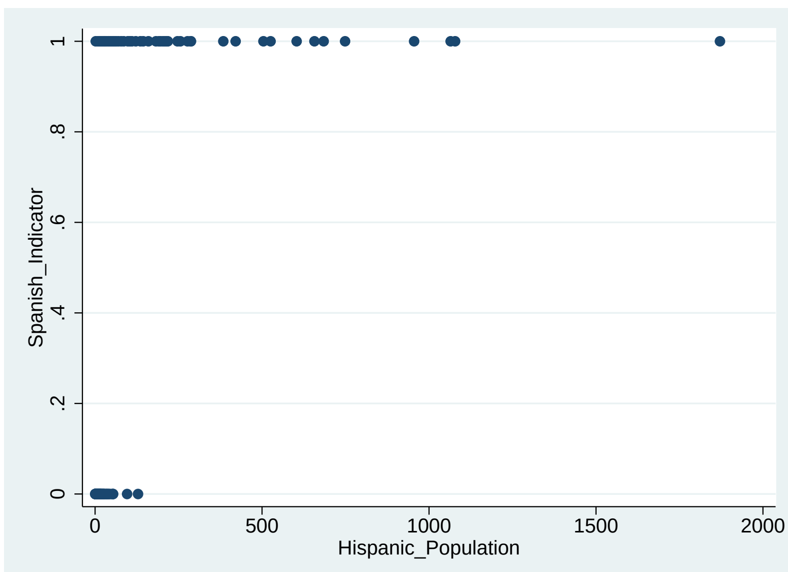


Figure 5: Presence of Spanish Station Plotted against Hispanic Metro Population, in 1000s (NYC, LA Excluded)

# E Tables

Table 1: Description of Market-Level Data

| Variable | Units | Mean | Std. Deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| Share in-metro | % | 0.111 | 0.026 | 0.030 | 0.151 |
| Share Out-metro | % | 0.015 | 0.023 | 0.000 | 0.104 |
| N1 (in-metro) | integer | 19.644 | 7.565 | 4.000 | 45.000 |
| N2 (out-metro) | integer | 7.209 | 8.320 | 0.000 | 37.000 |
| Population | millions | 1.016 | 1.687 | 0.075 | 14.481 |
| Ad Price | $ | 570.480 | 237.653 | 258.222 | 2691.177 |
| Income | 10,000$ | 4.584 | 0.860 | 2.482 | 8.010 |
| College | % | 21.200 | 5.370 | 10.200 | 37.100 |

Computed using the 163 markets with full data, see text.

Table 2: Classification of Formats into Ten Categories

| Format Group | Formats Included | | | | |
|---|---|---|---|---|---|
| **"Mainstream"** | Adult Cont. | Hot AC | Modern AC | Soft AC | Adult Altern. |
| | Classic Hits | 80s Hits | | | |
| **CHR** | CHR | | | | |
| **Country** | Country | Classic Cntry. | Trad. Country | | |
| **Rock** | Rock | Active Rock | Modern Rock | Classic Rock | |
| **Oldies** | Oldies | | | | |
| **Religious** | Religious | Cont. Christ. | Black Gospel | Gospel | S. Gospel |
| **Urban** | Urban | Urban AC | Urban Oldies | Rhythmic Old. | |
| **Spanish** | Spanish | Span.-Oldies | Span.-Adult Alt | Span.-C. Christ | Span.-CHR |
| | Span.-Cl. Hits | Span.-EZ | Span.-Hits | Span.-NT | Span.-Relig. |
| | Span.-Talk | Tejano | Tropical | Reg'l Mex. | Span.-Stand. |
| | Ranchero | Romantica | | | |
| **News/Talk** | News/Talk | News | Talk | Hot Talk | Bus. News |
| | Sports | Farm | | | |
| **Other** | Variety | Bluegrass | Blues | cp-new | Americana |
| | Pre-teen | Ethnic | Silent | A22 | A26 |
| | A30 | N/A | Jazz | Smooth Jazz | Dance |
| | Classical | Adult Stand. | Easy List. | | |

Table 3: Format Category Performance

| Format Group | Frequency* | Mean stations** | Max stations** | Mean format share** |
|---|---|---|---|---|
| **"Mainstream"** | 100.00% | 4.48 | 11 | 2.31% |
| **Rock** | 100.00% | 3.42 | 9 | 1.88% |
| **Country** | 99.39% | 2.99 | 9 | 1.85% |
| **News/Talk** | 100.00% | 4.31 | 13 | 1.55% |
| **Urban** | 73.62% | 2.10 | 6 | 1.24% |
| **CHR** | 93.25% | 1.66 | 6 | 1.16% |
| **Other** | 94.48% | 2.80 | 9 | 1.09% |
| **Oldies** | 98.16% | 1.48 | 5 | 0.79% |
| **Spanish** | 40.49% | 1.63 | 15 | 0.40% |
| **Religious** | 79.75% | 1.88 | 6 | 0.37% |

* Frequency with which a metro has at least one station (in- or out-metro) in format. ** Statistics computed over the 163 markets, both in- and out-metro taken into account.

Table 4: The listening equation - base case (horizontal differentiation)

| | | | | | |
|---|---|---|---|---|---|
| **Region Dummies** | northeast | 0.122*** | **Interactions** | hispXspan | 0.352*** |
| | | (0.042) | | | (0.036) |
| | midwest | 0.0974** | | blackXurban | 0.506*** |
| | | (0.041) | | | (0.050) |
| | south | -0.0506 | | southXreligious | 0.809*** |
| | | (0.041) | | | (0.095) |
| **Demographics** | black | -0.0681*** | | southXcountry | 0.316*** |
| | | (0.014) | | | (0.072) |
| | hisp | -0.0233** | **Correlation parameter** | $\sigma$ | 0.519*** |
| | | (0.0097) | | | (0.063) |
| | income | -0.00258 | **In-metro dummy** | | 0.639*** |
| | | (0.017) | | | (0.082) |
| | college | -0.0630** | **Constant** | | -5.325*** |
| | | (0.027) | | | (0.15) |
| **Format Dummies** | mainstream | 0.595*** | | | |
| | | (0.058) | | | |
| | chr | 0.431*** | | | |
| | | (0.056) | | | |
| | country | 0.389*** | | | |
| | | (0.053) | | | |
| | rock | 0.561*** | | | |
| | | (0.049) | | | |
| | oldies | 0.0447 | | | |
| | | (0.061) | | | |
| | religious | -1.264*** | | | |
| | | (0.072) | | | |
| | urban | -0.406*** | | | |
| | | (0.098) | | | |
| | spanish | -1.165*** | | | |
| | | (0.096) | | | |
| | nt | 0.214*** | | | |
| | | (0.053) | | | |
| Observations | 1919 | | | | |
| R-squared | 0.72 | | | | |

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: The listening equation - horizontal & vertical differentiation

| Parameter | Estimate | SE |
|---|---|---|
| **A. "First step" estimates (4,362 obs)** | | |
| $\kappa_1$ | 1.472 | 0.0063 |
| $\kappa_2$ | 1.134 | 0.0077 |
| **B. "Second step" estimates (1,253 obs)** | | |
| $\sigma$ | 0.589 | 0.017 |
| Constant | -5.143 | 0.007 |
| northeast | 0.097 | 0.008 |
| midwest | 0.067 | 0.010 |
| south | 0.088 | 0.011 |
| mainstream | 0.450 | 0.007 |
| chr | 0.438 | 0.007 |
| country | 0.617 | 0.007 |
| rock | 0.642 | 0.011 |
| oldies | 0.067 | 0.006 |
| religious | -0.954 | 0.004 |
| urban | -0.473 | 0.006 |
| spanish | -1.235 | 0.007 |
| nt | 0.189 | 0.004 |
| income/10 | -0.092 | 0.003 |
| college/10 | -0.656 | 0.001 |
| black/10 | -0.712 | 0.002 |
| hisp/10 | -0.370 | 0.003 |
| blackXurban/10 | 5.555 | 0.001 |
| hispXspan/10 | 3.962 | 0.002 |
| **C. Quality and Home effects*** | | |
| $\gamma^q$ | 0.604 | |
| $\gamma^h$ | 0.466 | |

* Computed by $\kappa_1(1-\sigma), \kappa_2(1-\sigma)$. See text.

Table 6: Advertisers' demand for listeners

| | OLS | IV |
|---|---|---|
| northeast | -0.0746 | -0.0739 |
| | (0.064) | (0.063) |
| midwest | 0.0835 | 0.0799 |
| | (0.061) | (0.059) |
| south | 0.0148 | 0.0132 |
| | (0.060) | (0.059) |
| income | 0.0567* | 0.0606** |
| | (0.030) | (0.029) |
| college | 0.167*** | 0.164*** |
| | (0.043) | (0.042) |
| black | -0.0231 | -0.0242 |
| | (0.021) | (0.020) |
| hisp | -0.0120 | -0.0124 |
| | (0.014) | (0.013) |
| $-\eta$ | -0.541*** | -0.510*** |
| | (0.062) | (0.072) |
| Constant | 4.492*** | 4.554*** |
| | (0.17) | (0.18) |
| Observations | 163 | 163 |
| R-squared | 0.52 | 0.52 |

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Optimal and observed market structures, base case (horizontal differentiation only)

| Format | Observed | Optimal | % Difference |
|---|---|---|---|
| Mainstream | 3.35 | 1.38 | 0.59 |
| CHR | 1.06 | 0.85 | 0.20 |
| Country | 2.10 | 1.05 | 0.50 |
| Rock | 2.33 | 1.09 | 0.53 |
| Oldies | 1.02 | 0.88 | 0.14 |
| Religious | 1.66 | 0.81 | 0.51 |
| Urban | 1.50 | 0.73 | 0.51 |
| Spanish | 1.34 | 0.60 | 0.56 |
| News/Talk | 3.08 | 1.35 | 0.56 |
| Other | 2.12 | 1.07 | 0.50 |
| **Total In-metro** | **19.58** | **9.79** | 0.50 |

Table 8: Bounding the optimal structures, base case (horizontal differentiation only)

| Format | Observed | Optimal (low) | Optimal (upp) | Optimal ("mid interval') |
|---|---|---|---|---|
| Mainstream | 3.35 | 1.29 | 1.60 | 1.38 |
| CHR | 1.06 | 0.85 | 0.86 | 0.85 |
| Country | 2.10 | 0.99 | 1.10 | 1.05 |
| Rock | 2.33 | 1.01 | 1.21 | 1.09 |
| Oldies | 1.02 | 0.85 | 0.88 | 0.88 |
| Religious | 1.66 | 0.75 | 0.90 | 0.81 |
| Urban | 1.50 | 0.68 | 0.77 | 0.73 |
| Spanish | 1.34 | 0.54 | 0.67 | 0.60 |
| News/Talk | 3.08 | 1.22 | 1.56 | 1.35 |
| Other | 2.12 | 1.01 | 1.19 | 1.07 |
| **Total In-metro** | **19.58** | **9.20** | **10.75** | **9.79** |

Table 9: Welfare analysis in the base case (horizontal differentiation only)

| | Observed | Optimal |
|---|---|---|
| Welfare ($ millions) | 11,977 | 13,779 |
| Mean In-Metro Listening Share (%) | 11.10% | 8.15% |
| Mean Ad Price ($) | 570.48 | 662.54 |

Table 10: Optimal and observed market structures, horizontal and vertical differentiation

A. Formats with a single quality level:

| | Mean number observed | Mean number optimal | Mean optimal reduction |
|---|---|---|---|
| CHR | 1.06 | 0.85 | 20.2% |
| Country | 2.10 | 1.02 | 51.3% |
| Rock | 2.33 | 1.04 | 55.3% |
| Oldies | 1.02 | 0.86 | 16.2% |
| Religious | 1.66 | 0.77 | 53.5% |
| Urban | 1.50 | 0.71 | 52.6% |
| Spanish | 1.34 | 0.50 | 63.0% |
| Other | 2.12 | 1.01 | 52.3% |

B. Formats with quality differentiation:

| Format: | Mainstream | | News/Talk | |
|---|---|---|---|---|
| | Low quality | High quality | Low quality | High quality |
| Mean number observed | 1.18-1.95 | 1.40-2.17 | 1.83-2.02 | 1.06-1.25 |
| Mean number optimal | 0.37-0.66 | 0.56-0.86 | 0.79-0.89 | 0.40-0.51 |
| Mean optimal reduction | 44.1%-81% | 38.6%-74.2% | 51.3%-61.2% | 51.7%-67.6% |

Table 11: Comparing Symmetric vs. Nonsymmetric Specifications

| | Symmetric | Non-Symmetric | | Symmetric | Non-Symmetric |
|---|---|---|---|---|---|
| northeast | 0.122*** | 0.139*** | hispXspan | 0.352*** | 0.286*** |
| | (0.042) | (0.027) | | (0.036) | (0.018) |
| midwest | 0.0974** | 0.100*** | blackXurban | 0.506*** | 0.460*** |
| | (0.041) | (0.026) | | (0.050) | (0.029) |
| south | -0.0506 | -0.0906*** | southXreligious | 0.809*** | 1.034*** |
| | (0.041) | (0.026) | | (0.095) | (0.061) |
| black | -0.0681*** | -0.0467*** | southXcountry | 0.316*** | 0.274*** |
| | (0.014) | (0.0090) | | (0.072) | (0.048) |
| hisp | -0.0233** | -0.0153** | $\sigma$ | 0.519*** | 0.614*** |
| | (0.0097) | (0.0063) | | (0.063) | (0.034) |
| income | -0.00258 | 0.0233** | FM | | 0.305*** |
| | (0.017) | (0.011) | | | (0.030) |
| college | -0.0630** | -0.0797*** | power100 | | 0.367*** |
| | (0.027) | (0.017) | | | (0.033) |
| home | 0.639*** | 0.325*** | HAAT1000 | | 0.0537*** |
| | (0.082) | (0.031) | | | (0.016) |
| mainstream | 0.595*** | 0.296*** | FMXnt | | -0.237*** |
| | (0.058) | (0.039) | | | (0.064) |
| chr | 0.431*** | 0.0306 | Constant | -5.325*** | -5.247*** |
| | (0.056) | (0.038) | | (0.15) | (0.094) |
| country | 0.389*** | 0.0939** | | | |
| | (0.053) | (0.038) | | | |
| rock | 0.561*** | 0.238*** | | | |
| | (0.049) | (0.033) | | | |
| oldies | 0.0447 | -0.331*** | | | |
| | (0.061) | (0.042) | | | |
| religious | -1.264*** | -1.336*** | | | |
| | (0.072) | (0.052) | | | |
| urban | -0.406*** | -0.556*** | | | |
| | (0.098) | (0.062) | | | |
| spanish | -1.165*** | -1.044*** | | | |
| | (0.096) | (0.058) | | | |
| nt | 0.214*** | 0.320*** | | | |
| | (0.053) | (0.032) | | | |
| Observations | 1919 | 4362 | | | |
| R-squared | 0.72 | 0.79 | | | |

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Probit Results for Formats

| | Urban | Spanish | Religious |
|---|---|---|---|
| Population (000s) | 0.0005 | -0.00251*** | -0.0003 |
| | (0.00088) | (0.00069) | (0.00047) |
| income | -0.121 | 0.628* | 0.275 |
| | (0.27) | (0.35) | (0.23) |
| Black Population (000s) | 0.0338*** | 0.00319 | 0.0116** |
| | (0.0095) | (0.0023) | (0.0046) |
| Hispanic Population (000s) | -0.0022 | 0.0741*** | -0.0004 |
| | (0.0019) | (0.014) | (0.0014) |
| college | 0.0588 | -0.501 | -0.367 |
| | (0.36) | (0.42) | (0.28) |
| northeast | 0.772 | 0.934 | -0.212 |
| | (0.50) | (0.72) | (0.43) |
| midwest | 0.243 | 1.322* | -0.394 |
| | (0.48) | (0.73) | (0.40) |
| south | 1.348*** | 1.866** | 0.369 |
| | (0.52) | (0.79) | (0.41) |
| Constant | -0.855 | -4.385*** | -0.0618 |
| | (0.99) | (1.60) | (0.89) |
| Observations | 163 | 163 | 163 |

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Restricting Attention to “Selection-free” Sub-samples

| | Full sample | ”Urban Subsample” | ”Spanish Subsample” | ”Religious Subsample” |
|---|---|---|---|---|
| $\sigma$ | 0.519*** | 0.656*** | 0.390** | 0.765*** |
| | (0.063) | (0.11) | (0.17) | (0.19) |
| black | -0.0681*** | -0.0311 | -0.0767 | -0.0424 |
| | (0.014) | (0.024) | (0.051) | (0.044) |
| hisp | -0.0233** | -0.0287 | -0.0194 | -0.0121 |
| | (0.0098) | (0.019) | (0.017) | (0.025) |
| income | -0.00258 | 0.00917 | 0.0680* | 0.0588 |
| | (0.017) | (0.026) | (0.039) | (0.064) |
| college | -0.0630** | -0.125*** | -0.209*** | -0.127 |
| | (0.027) | (0.042) | (0.073) | (0.12) |
| home | 0.639*** | 0.432*** | 0.699*** | 0.328 |
| | (0.083) | (0.16) | (0.21) | (0.30) |
| mainstream | 0.595*** | 0.803*** | 0.150 | 0.887*** |
| | (0.058) | (0.099) | (0.095) | (0.17) |
| chr | 0.431*** | 0.383*** | -0.183 | 0.250 |
| | (0.056) | (0.084) | (0.23) | (0.17) |
| country | 0.389*** | 0.163* | -0.323** | -0.408** |
| | (0.054) | (0.094) | (0.15) | (0.20) |
| rock | 0.561*** | 0.635*** | -0.0104 | 0.616*** |
| | (0.049) | (0.077) | (0.097) | (0.13) |
| oldies | 0.0447 | -0.0100 | -0.380* | 0.00510 |
| | (0.062) | (0.099) | (0.22) | (0.20) |
| religious | **-1.264*** ** | -1.238*** | -1.627*** | **-1.244*** ** |
| | (0.073) | (0.11) | (0.23) | (0.21) |
| urban | **-0.406*** ** | **-0.173** | -0.458** | -0.250 |
| | (0.099) | (0.14) | (0.23) | (0.30) |
| spanish | **-1.165*** ** | -1.311*** | **-1.369*** ** | -1.226*** |
| | (0.097) | (0.14) | (0.17) | (0.22) |
| nt | 0.214*** | 0.494*** | -0.0702 | 0.669*** |
| | (0.054) | (0.091) | (0.096) | (0.16) |
| hispXspan | **0.352*** ** | 0.550*** | **0.271*** ** | 0.564*** |
| | (0.036) | (0.085) | (0.055) | (0.12) |
| blackXurban | **0.506*** ** | **0.461*** ** | 0.345*** | 0.554*** |
| | (0.051) | (0.067) | (0.13) | (0.14) |
| southXreligious | **0.809*** ** | 0.982*** | -0.0883 | **0.954*** ** |
| | (0.095) | (0.14) | (0.18) | (0.24) |
| southXcountry | 0.316*** | 0.614*** | 0.306** | 1.108*** |
| | (0.072) | (0.11) | (0.14) | (0.22) |
| Constant | -5.325*** | -5.031*** | -5.195*** | -5.161*** |
| | (0.15) | (0.28) | (0.46) | (0.55) |
| Observations | 1919 | 846 | 444 | 341 |
| R-squared | 0.72 | 0.72 | 0.73 | 0.66 |

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Regional effects not reported for lack of space.

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