Music Variety, Station Listenership and Station Ownership in the Radio Industry

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Abstract

This paper examines how changes in radio station ownership have affected music variety and station listenership. A unique panel dataset of music radio airplay shows that a common owner of stations in the same local radio market and the same broad music category increases the degree of differentiation between these stations, consistent with only a common owner internalizing "business stealing" effects. The implied effect on playlists is quite large and is not captured by changes in stations' formats. Common ownership of stations in the same category but different local markets results in, at most, a small degree of playlist homogenization. Panel data on station listenership provides further support for the business stealing explanation, as when stations in a local market become commonly owned their audiences tend to increase.

1 Introduction

If product characteristics can be changed easily then mergers may affect welfare through changing product variety or product quality rather than prices. The effect on variety of radio station mergers, both between stations in the same local radio market and between stations in different markets, has been the subject of considerable debate since the relaxation of ownership restrictions in the 1996 Telecommunications Act.[1]

I use new data on the artists and songs played by music radio stations from 1998 to 2001 to provide new evidence on the effects of ownership. Common ownership of stations in the same metro-market and music category (hereafter I denote a metro-market category by MMC) is associated with greater differentiation in station playlists. I find this result both when I look across metro-markets with different ownership structures and when I examine how changes in station ownership affect the playlists of particular stations. This effect is robust to different measures of station location and it is quite large in magnitude. For example, using a measure of station location that takes into account that some artists are alike and others are not, I find that when a pair of stations in an MMC become commonly owned they move 13% further apart. On the other hand, common ownership of stations in different metro-markets is associated with, at most, a small homogenization of playlists.

The finding that a common owner increases the degree of differentiation between local stations is consistent with only a common owner internalizing "business stealing" effects. If this is the primary effect of common ownership then one would also expect station listenership to increase. Panel data on station listenership provides some evidence that when stations in an MMC become commonly owned their combined audience does indeed tend to increase. However, the size and statistical significance of the audience effect are sensitive to the specification used and, in particular, to how the degree of substitution between stations in different categories is estimated.

[1] Critics of consolidation have been particularly concerned about homogenization in music e.g., DiCola and Thomson (2002) on behalf of the Future of Music Coalition, rebutted by the National Association of Broadcasters (2002).

Before describing the relationship between this paper and the existing literature on broadcasting variety, I define two terms which I use to classify a station's programming genre. I use a classification of stations from BIAfn's *Media Access Pro* database which is also used by the Federal Communications Commission (e.g., FCC (2001a), (2001b)). A *format* is the narrowest classification of a station's genre. An example of a music format is "Hot Adult Contemporary". A *category* groups together similar formats. Each format belongs to one category. Stations in the Adult Contemporary, Hot Adult Contemporary and Soft Rock formats are among 24 formats in the Adult Contemporary (AC) category. Table 1 lists the seven music categories which are the focus of most of this paper and the main formats in each category. There are several significant formats in Adult Contemporary and Rock, whereas almost all Country category stations are in the Country format. In analyzing variety, I compare the playlists of stations which are in the same category but possibly different formats.

This is not the first paper to study the effect of radio mergers on variety. Berry and Waldfogel (2001) find that counts of the number of formats and the number of formats per station in each metro-market increased more, following the 1996 Telecommunications Act, in the largest metro-markets where the Act allowed more mergers. They interpret this result as providing evidence that within-market mergers increase variety.[2] On the other hand, they also find that commonly owned stations within a market tend to be clustered in similar, but different, formats suggesting that variety increases might be limited to prevent leaving gaps in product space which might attract entry. My result that within-market mergers increase product differentiation is similar to Berry and Waldfogel's result, but I use a quite different empirical method which reveals an important limitation in using formats to measure variety. The station-level playlist data shows that stations in the same format can play quite different artists and that stations in different formats can play similar artists. This is not entirely surprising as a format is simply a label which a station assigns to itself. I use actual changes in station ownership, rather than the natural experiment of the 1996 Act, to examine how ownership affects a station's

[2] George (2001) provides evidence that within-market mergers in the newspaper industry increase variety using data on the beats covered by journalists.

playlist relative to other stations in its category. I find that within-MMC mergers increase variety but very little of this effect is reflected in changes in station formats.[3]

Two studies have used playlist data. Williams et al. (2002), as part of the FCC's assessment of its ownership rules, use data on the top 10 most played songs on 174 stations in March 1996 and March 2001. They conclude that variety increased within metro-market formats over time without a clear relationship with station ownership. However, they do not look specifically at the effect of common ownership on stations in the same market and in the same or similar formats which are most likely to compete for the same listeners. Chambers (2003) uses a one week cross-section of airplay data from March 2002 and finds that metro-markets with more concentrated ownership tend to play fewer songs which are more than one year old. He interprets this as indicating that ownership consolidation reduces within-market diversity even though there is no significant relationship for younger songs. In contrast, I find that within-MMC mergers do tend to increase variety using a much richer panel dataset and several measures of product differentiation. I also show that there is only very limited evidence of homogenization resulting from common ownership across markets.

The second part of the paper tests whether the listenership of local stations which become commonly owned increases, consistent with product differentiation increasing because a common owner internalizes business stealing. Berry and Waldfogel (1999a) and Rogers and Woodbury (1996) provide evidence of business stealing in radio using cross-sections of listenership data from different markets prior to ownership liberalization. Borenstein (1986) provides weak evidence of business stealing by examining station entry and exit in the largest 5 metro-markets from 1975 to 1984. Berry and Waldfogel (1999b) find no systematic relationship between changes in aggregate market listenership and the number of formats after the 1996 Act. I examine what happens to the audience of *individual stations* following ownership changes and find some evidence that common ownership increases station

[3] I note that because I use a different format classification to Berry and Waldfogel it is possible that airplay changes would have been captured by format changes in their classification. However, this is unlikely because my classification has more formats than the classification used by Berry and Waldfogel.

audiences. I also devise a test, using the fact that some stations have listeners in multiple markets, which shows that these audience increases are more likely to be explained by increased product variety than improvements in absolute station quality or reduced advertising.

Section 2 reviews the main theories of product differentiation which are relevant to radio. Section 3 provides the empirical analysis of product differentiation and Section 4 presents the empirical analysis of listenership. Section 5 concludes.

2 The Theory of Product Differentiation in Radio

A small theoretical literature has examined the incentives for product differentiation in advertiser-funded broadcasting.[4] Section 2.1 informally summarizes how these incentives may change when local competitors become commonly owned. Section 2.2 provides a simple model of music research to show how common ownership of stations playing similar music in different metro-markets may lead to playlist homogenization. The footnotes illustrate that the effects are recognized in the industry using quotes from *Billboard* magazine.

2.1 Effect of Common Ownership of Local Competitors on Product Differentiation

Consider a simple situation in which station B is fixed at the origin and station A chooses its location, a, on the positive real line. I assume that station owners maximize commercial revenues (π) and that, for station A, $\pi_A = pc_A L_A(a, c_A, c_B)$ where c_i is i's quantity of commercials, L_i is i's audience and p is the price per listener per commercial. A common owner of A and B sets a to maximize $\pi_A + \pi_B$ whereas a separate owner sets a to maximize π_A.

[4] For example, Steiner (1952), Spence and Owen (1977), Gabszewicz et al. (1999) and Anderson and Coate (2000).

2.1.1 Business Stealing Effect[5]

Initially assume that c_A, c_B and p are fixed and that A's optimal location (a^*) is a unique solution to first-order conditions. a^* satisfies (1) under separate ownership and (2) under common ownership.

$$\frac{\partial \pi_A}{\partial a} = pc_A \frac{\partial L_A(a^*, c_A, c_B)}{\partial a} = 0 \tag{1}$$

$$\frac{\partial(\pi_A + \pi_B)}{\partial a} = pc_A \frac{\partial L_A(a^*, c_A, c_B)}{\partial a} + pc_B \frac{\partial L_B(a^*, c_A, c_B)}{\partial a} = 0 \tag{2}$$

Assuming that $\frac{\partial L_B(a, c_A, c_B)}{\partial a} > 0$ (B's audience falls when A locates closer to B), A locates further from B under common ownership because it internalizes business stealing. If $c_A = c_B$, a common owner simply maximizes the stations' combined audience, so this will increase under common ownership.

2.1.2 Strategic Location Choice with Endogenous Quantities of Commercials

Now assume that p is fixed but that c_A and c_B are chosen in the second stage of a two-stage game. In the first stage A chooses a. Assuming that $\frac{\partial L_i(a, c_i, c_j)}{\partial c_i} < 0$ and $\frac{\partial L_i(a, c_i, c_j)}{\partial c_j} > 0$ (listeners dislike commercials), this resembles a standard game of price competition on a line in which firms choose locations before setting prices. Under separate ownership, A may strategically choose to locate away from B to soften competition in setting c_A and c_B in the second stage (Tirole (1988), p. 281-282). A common owner, who sets c_A and c_B to maximize joint profits in the second stage, has no need for strategic differentiation. The comparison of differentiation under different ownership structures depends on the relative sizes of the business stealing and strategic differentiation incentives.

The internalization of business stealing tends to increase the combined audience but it may fall if a common owner plays more commercials. On the other hand, if p is not fixed and a common owner

[5] *Billboard* (February 22 2003), Clear Channel's Memphis Director of Urban Programming, "I can't play Luther Vandross, because he needs to play on my adult R&B, KJMS; I need to drive listeners there. If I'm playing him on my mainstream [WHRK], what reason do listeners have to tune in to KJMS?" *Billboard* (October 14 2000), an Infinity Programming Director in Cleveland, "We're far more focused on a specific part of the audience. Before, you could attract a certain demo, knowing full well there would be a spill-over of audience. Now we're more target orientated...you want to win the battle and beat [your sister stations] but not kill them."

reduces c_A and c_B in order to raise the price of commercials then the combined audience will increase because the business stealing and advertising effects work in the same direction. This leads to the possibility that increases in listenership following mergers may reflect reduced advertising rather than increased variety.

2.1.3 Entry Deterrence[6]

As discussed by Berry and Waldfogel (2001), the possibility of future entry can also affect A's location decision. Suppose that once a has been chosen a potential entrant, independently owned and with some randomly drawn sunk costs of entry, chooses whether to enter between A and B. A now takes into account how its location decision will affect the profitability of entry. A considers how entry would reduce the revenues of both A and B under common ownership. Entry may cause a particularly large reduction in revenues when A and B are commonly owned if it restores competition in setting c_A and c_B. Therefore which ownership structure provides greater variety depends on the relative sizes of the entry deterrence, business stealing and strategic differentiation incentives.

2.2 Effect of Common Ownership of Stations in Different Metro-Markets on Product Differentiation[7]

The internalization of business stealing is only relevant for stations competing for the same listeners. However, many radio groups own stations in different metro-markets and I use a simple model to show how this could lead to homogenization of station playlists.

[6] *Billboard* (October 14 2000), an Infinity Programming Director in Cleveland, "I initially made that mistake when I was programming KPNT (The Point) in St. Louis. We made sure The Point and [sister station] The River were programmed so far away from each other that you could drop something in the middle of them and that's what the competition wants you to do."

[7] *Billboard* (November 16 2000) "At Infinity Radio - with more than 180 stations - regular conference calls are held, with programmers from similarly formatted stations discussing what music is working in their markets. This networking is intended to allow programers to maintain control, while enhancing the information upon which they base music decisions." Senior Vice President Programming at Clear Channel Communications (quoted in same article) "Generally local PDs have complete authority with respect to music additions. They are encouraged to consult with their brand managers and share relevant research data as part of the decision process." Ahlkvist and Fisher (2000) conclude that "group ownership plays a modest role in standardizing music programming; its effect on standardization is mediated only by research and consultant use" (p. 320).

Suppose that A and B are in the same music category but different metro-markets and that each station is deciding which of two songs, S_1 and S_2, to add to its playlist. In each market one song is a better match for local tastes and a station gets a benefit of $\Psi > 0$, from a larger audience, if it picks the better match. Tastes are imperfectly correlated across markets so that if S_i is a better match in one market then it is a better match in the other market with probability $\lambda \geq \frac{1}{2}$. Before adding a song, each station can use a local market research technology to improve its information about listener tastes in its market. Prior to any research, each station assigns a probability of $\frac{1}{2}$ to each song being the better match in its market. The research technology consists of the ability to do a succession of projects (indexed 1,2,3,...). Each project is successful with probability $p < 1$ in which case it reveals correctly the identity of the better match and otherwise it gives no information. Each successive research project costs more, so that there are declining returns to research expenditure, and a station sees the results of each project before deciding whether to do the next one. Separately owned stations cannot share research results but commonly owned stations can without cost, and they can wait for the result of a research project on one station before deciding whether to do more research on the other station.[8] A station with a research success chooses to play the better matched song. A common owner with a success on only one station will choose the same song on both stations if $\lambda > \frac{1}{2}$. A station with no information on which is the better match chooses each song with equal probability.

It is straightforward to show that if $\lambda > \frac{1}{2}$ then the stations are more likely to choose the same song under common ownership.[9] For given research strategies on each station, the ability to share information under common ownership leads immediately to this result but two other effects work in

[8] The key assumption is that separately owned stations do not give each other research results for free. This is a sensible assumption because a station has a competitive incentive to avoid giving any successful research to a third party who might pass it on to one of its metro-market competitors.

[9] A sketch of the proof: under separate ownership the probability of choosing the same song is λ if both stations have a success and $\frac{1}{2}$ otherwise. Under common ownership it is λ if they both have a success, 1 if only one of them has a success and $\frac{1}{2}$ otherwise. The probability of choosing the same song is therefore certainly higher under common ownership if the probability of at least one station having a success is higher under common ownership. This is follows from comparing the expected marginal benefits of doing a particular project on an unsuccessful to date separately owned station and on a commonly owned station when both of the stations have been unsuccessful to date. In particular, the expected marginal benefit of the last project which a separately owned station would choose to undertake is $\frac{p\Psi}{2}$ whereas a commonly owned station would have an expected marginal benefit from undertaking the same project of $p\lambda\Psi$. The common owner therefore has more incentive to continue to do research until he gets a success if $\lambda > \frac{1}{2}$.

the same direction. First, a common owner has more incentive to do research until one station has a research success, because the first success benefits both stations. Second, a common owner has less incentive to achieve a second success, which could lead to the stations making different choices, because, with $\lambda > \frac{1}{2}$, a second research success is likely to simply confirm the first research result.[10] Expected station payoffs are higher under common ownership because research information is used more efficiently. If tastes are uncorrelated across markets then research strategies are the same under either ownership structure.

3 Does Common Ownership Increase Music Variety?

I use a panel of music radio airplay data to analyze how station ownership and changes in station ownership affect product differentiation within music categories. Section 3.1 describes the data, Section 3.2 details three measures of a station's location in product space, Section 3.3 describes the main specification used, Section 3.4 provides summary statistics and Section 3.5 presents the results.

3.1 Airplay Data

Mediabase 24/7, a company which collects music radio airplay data for the music and radio industries, generously provided me with access to a sample of daily airplay logs from 1,095 contemporary music radio stations for the first week (Monday-Friday) of each month from April 1998 to December 2001. A log is a list of the artist, song-title and release year for each song played. I define a station's location in product space using the number of times each artist or each artist-song title combination was played. This ignores the role of non-music programming in affecting differentiation, but the choice of music is undoubtedly the most important characteristic of a music station's product.[11]

[10] Note that this may mean that the stations are more likely to select the better matched song under separate ownership. In particular, this happens when, under separate ownership, the stations do enough research to find the better match with close to certainty. The socially prefered ownership structure then depends on how much of listeners' valuations from listening to the better matched song are captured by stations in Ψ.

[11] I note three features of how artists or artist-song title combinations are defined: recordings of the same song by different artists are treated as different artist-song title combinations; a singer is treated as a separate artist when

The 1,095 stations are drawn from 7 categories and 148 Arbitron-defined metro-markets. The 7 categories are Adult Contemporary (AC), Album Oriented Rock/Classic Rock (AOR), Contemporary Hit Radio/Top 40 (CHR), Country, Oldies, Rock and Urban.[12] A station's category in a given week is based on its format for the relevant Arbitron ratings period listed in BIAfn's *Media Access Pro* database together with BIAfn's Fall 2001 classification of formats into categories. Arbitron gives every rated station a home metro-market which is typically the market in which it attracts most of its listeners. The airplay sample does not include every station in these 7 categories in the 148 metro-markets but the sample stations account for the vast majority of listening in their MMCs, as shown in Table 2. Coverage is particularly good in larger metro-markets. There are few Oldies stations, especially in smaller markets.

The panel is unbalanced in several dimensions. Mediabase's sample of stations and markets expands over time and a few stations exit in 2001 due to changing categories. For some weeks I do not have 5 days of data: in particular, I have only 1 day of data for any station in 11 weeks in 1998 and 1999 (10 of them in 1999), 4 days for 3 weeks and a full 5 days for 31 weeks (including all but 1 week in 2000 and 2001). A large number of individual station days are also missing for reasons that should not be correlated with airplay. Table 3 provides some summary statistics on the structure of the panel. Overall, there are 35,750 station-weeks of airplay data.

3.2 Measures of Station Location

I use the airplay data to locate stations in product space. As stations update playlists every week or so, I aggregate the daily logs to give weekly playlists. If a station has one or more days of data missing then its weekly playlist is based only on the remaining days. I examine the relative location of stations *in the same category* and do not consider the relative locations of stations in different categories. The

recording as an individual or as part of a group; and, Mediabase groups some different songs together under the title "Christmas Music" with artist as "Various". I treat these as a single artist-song title combination but the results are completely unaffected if I drop all December observations.

[12] The music categories for which I do not have airplay data are Classical, Easy Listening, Jazz and Nostalgia/Big Band.

assumption is that stations in different categories do play different kinds of music and that if stations choose their playlists strategically then their locations are primarily affected by the choices of stations playing similar music.

Given the richness of the airplay data, there are many ways to locate stations. I show that three different measures give qualitatively similar results. For the first two measures, each artist or each artist-song title combination defines a different dimension of the product space. This treats each artist as being equally like or unlike any other artist, which ignores potentially useful information. For example, Elton John, Phil Collins and U2 are all heavily played by Adult Contemporary stations but most listeners would probably say that Elton John and Phil Collins are more like each other than U2. My third measure locates artists and stations in a plane with similar artists located close together.

Measure 1: each artist is a separate dimension of product space. Every artist played by any station in the category during the week defines an orthogonal dimension of product space. A station's location is defined by each artist's share of its playlist. For example, if there are only three artists (X, Y and Z) and station i plays X, Y and Z 10, 0 and 5 times respectively then i's (X,Y,Z) location is $(\frac{2}{3}, 0, \frac{1}{3})$. A station plays, on average, over 177 different artists during a 5 day week and the stations in a category together play over 1,200 different artists. The distance between two stations is defined as the angle (in radians) between their location vectors, so the distance between two stations with no artist in common is $\frac{\pi}{2}$.[13]

Measure 2: each artist-song title combination is a separate dimension of product space. This is the same as Measure 1, except that each artist-song title combination defines an orthogonal dimension of the product space. A station plays, on average, over 395 different artist-song title combinations during a 5 day week.

[13]For two stations i and j with location vectors v_i and v_j the distance is given by $\arccos\left(\frac{v_i.v_j}{\|v_i\|\|v_j\|}\right)$ where $v_i.v_j$ is the dot product of the vectors. There is an alternative interpretation of this distance. Suppose that each station's location in artist space is projected onto the unit hypersphere with number of dimensions equal to the number of artists. The distance between the stations is equal to the the shortest distance between the two stations along the surface of the hypersphere.

Measure 3: location in a 2-dimensional plane allowing some artists to be more similar than others. Stations are located using a 2-step procedure. In the first step, the artists played in a category-week are located in a 2-dimensional plane.[14] I assume that artists played heavily by the same stations are more similar (closer together in product space) than those played heavily by different stations. For example, Elton John, Phil Collins and U2 are played heavily by Adult Contemporary (AC) category stations but most listeners would probably say that Elton John and Phil Collins are more similar to each other than they are to U2. In November 2001 the correlation of plays of Elton John and Phil Collins on AC stations was 0.8214 and the correlation of Elton John and U2 was -0.6631. I first locate each artist in high-dimensional station space in a similar way to the location of stations for Measure 1 with each station defining a separate and orthogonal dimension of the product space. I then calculate the distance between each pair of artists as the angle (in radians) between their location vectors and project each artist into a 2-dimensional plane. The projection aims to minimize

$$\sum_{i=1}^{A-1} \sum_{j=i+1}^{A} \left(d_{ij} - \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \right)^2 \qquad (3)$$

where d_{ij} is the high-dimensional distance between artists i and j, A is the number of different artists played by any station in the category-week and (x_i, y_i) are the coordinates of artist i in the plane which are to be estimated. I fix the most played artist at the origin and fix the second most played artist on the x-axis. Artists are located relative to each other and the axes have no direct interpretation.

Of course, 1,200 artists in a category-week would give 2,397 parameters so (3) cannot be minimized for all artists simultaneously. I reduce the problem slightly by dropping all artists played less than 10 times in the category-week. Appendix A describes the exact procedure used to locate the remaining

[14] I note that an alternative would be to locate all artists only once and assume that their locations do not change during the sample period. In some categories this would make sense, but in categories such as Contemporary Hit Radio/Top 40 this would make it hard to differentiate between stations which only play very recent releases and those which play slightly older releases because sometimes a pair of artists might release songs at the same time and at other times they might release them at different times. I note that in categories such as Adult Contemporary the estimated relative locations of major artists are very similar each week.

artists: I first locate the 30 most played artists (accounting for, on average, over 42% of plays in a category-week) and then sequentially locate the remaining artists.

This procedure produces a highly plausible pattern of artist locations. Figure 1 shows the estimated locations of the 30 most played artists in the AC category in the first week of November 2001. Elton John (the most played artist) is at the origin. The maximum distance between artists in the high-dimensional space is 1.5708 so artists who are roughly this distance apart in the plane such as Rod Stewart and the Dave Matthews Band are rarely played together. Elton John, Phil Collins, Rod Stewart and Billy Joel are located close to each other while U2 are located closer to the Dave Matthews Band and Jewel.

In the second step, I locate each station at the weighted average of the coordinates of the artists with the weights equal to the share of each artist in its playlist. Continuing the Measure 1 example, if artist X is located at (0,0), Y at (1,0) and Z at $(-\frac{1}{3}, \frac{1}{2})$ then station i is located at $(-\frac{1}{9}, \frac{1}{6})$. 5 station-week playlists which do not contain any artist played at least 10 times in the category-week are dropped. The distance between stations is the straight line distance in the plane.

Figure 2 shows the implied locations of AC stations in the first week of November 2001 together with some of the artists from Figure 1. Stations in different formats have different symbols to show how well formats reflect differences in the music stations play.[15] Soft AC, Lite AC and Soft Rock stations are clustered near Elton John and Celine Dion whereas Hot AC and Modern AC stations are located closer to U2, the Dave Matthews Band and Smash Mouth. While stations in the same format do tend to play more similar music than stations in different formats there is considerable heterogeneity in the locations of stations in some formats, such as Adult Contemporary, and stations in some different formats such as Lite AC, Soft AC and Soft Rock are located very close together showing that these

[15] The airplay stations come from 77 different BIAfn formats. I rationalize these 77 formats into 34 different formats, aggregating those formats which have only a few station-week observations in the airplay data and which are clearly very similar to some other formats. For example, I group Rhythmic, Rhythmic/AC, Rhythmic/CHR, Rhythmic/Hot AC, Rhythmic/Oldies and Rhythmic/Top 40 into a Rhythmic format. The results are qualitatively the same under several different aggregations or using no aggregation at all. Using 34 specific formats for these 7 contemporary music categories allows for more formats than Berry and Waldfogel (2001) who allowed 45 formats for all of radio (19 BIAfn music and non-music categories).

Figure 1: 30 Most Played Artists on Stations in the Adult Contemporary Category in the First Week of November 2001 Located in 2-Dimensional Music Product Space

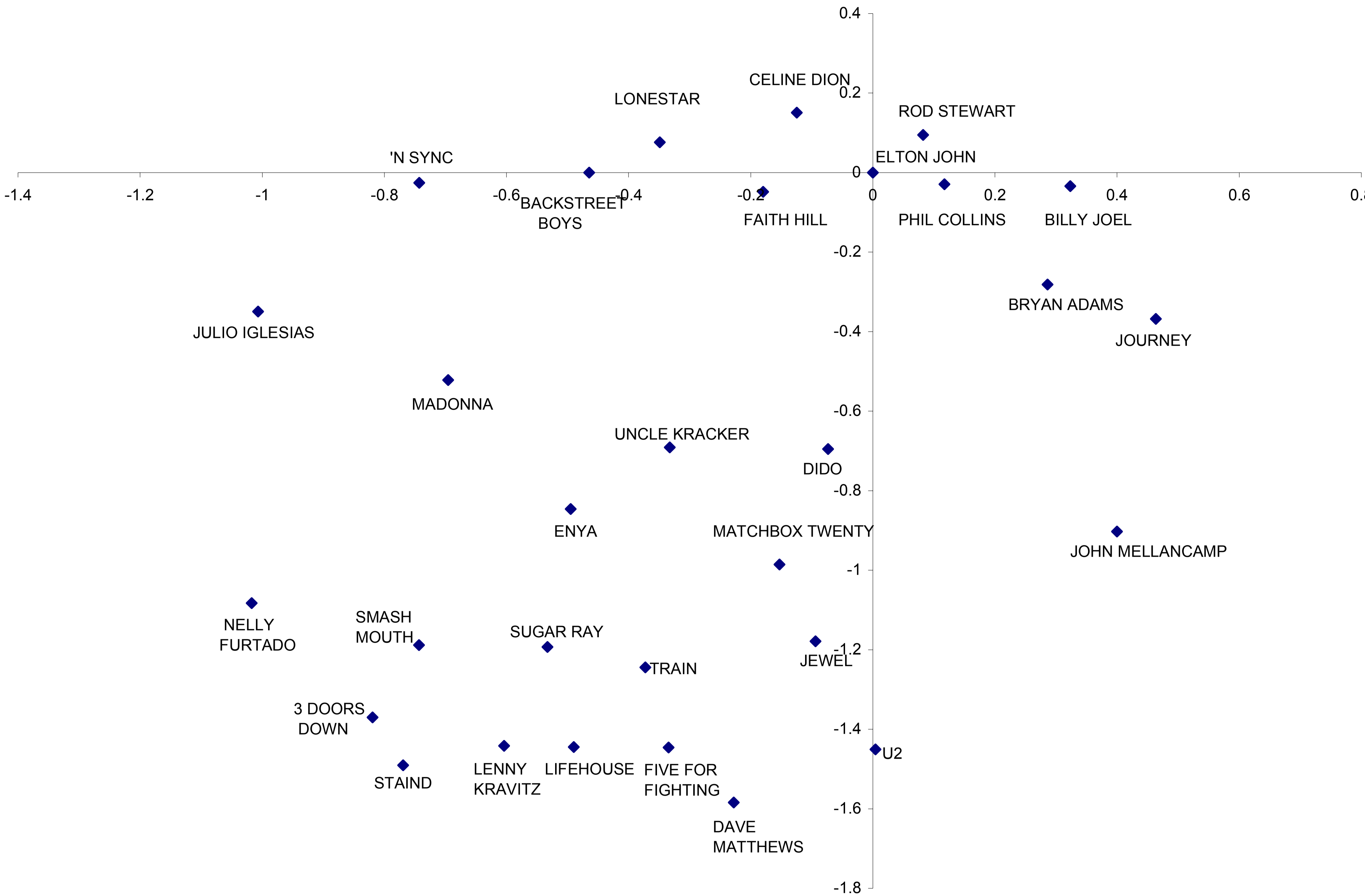
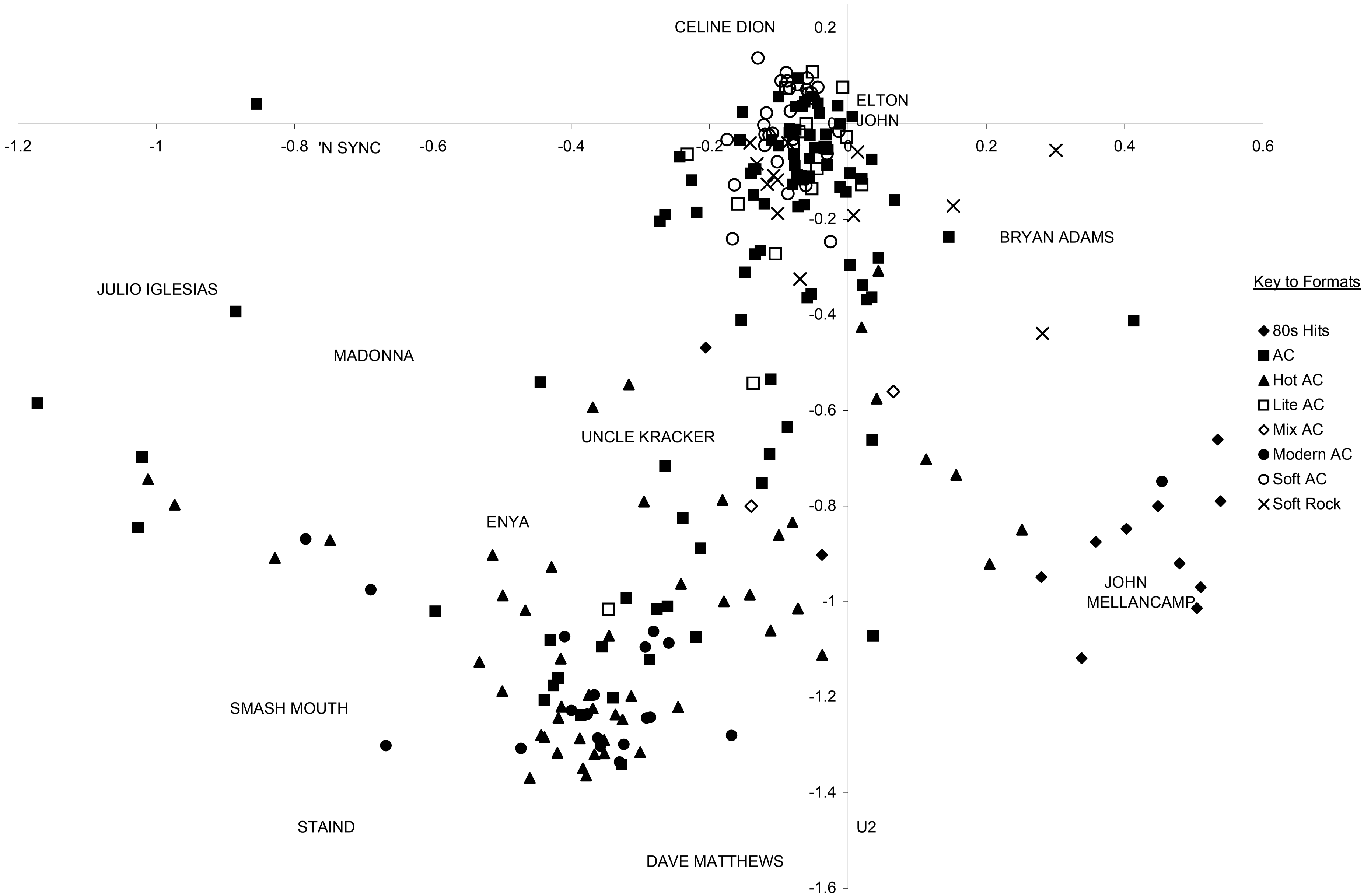


Figure 2: Stations in the Adult Contemporary Category Located in 2-Dimensional Music Product Space, based on Artist Playlists in the First Week of November 2001 plus Selected Artist Locations



formats are very similar.[16] This suggests that formats provide some information on variety but that individual station airplay data allows a much more precise analysis.

3.3 Regression Specification

The main specification examines how the distance between pairs of stations in the same category varies with ownership and whether the stations are in the same market. The linear specification is

$$y_{ijw}^{PAIR} = X_{ijw}\beta_1 + C_{ijw}\beta_2 + W_w\beta_3 + \varepsilon_{ijw} \tag{4}$$

where y_{ijw} is the distance between stations i and j in week w, C_{ijw} are dummy variables for the category, W_w are dummy variables for different weeks and ε_{ijw} is an error term. X contains the following dummy variables:

$SAME\_REGION$ is 1 if i and j are home to metro-markets in the same one of BIAfn's 9 geographic regions. Regional music tastes may lead to stations in the same region playing similar music.

$SAME\_MARKET$ is 1 if i and j are home to the same metro-market. The coefficient measures how much further apart stations in the same metro-market are than a pair of separately owned stations from the same region and the same category.

$SAME\_OWNER$ is 1 if i and j have the same owner in week w. BIAfn's database gives a transaction history for each station.[17] The coefficient measures how much further apart commonly owned stations in different metro-markets are than separately owned stations in different markets.

[16] Of course, one might believe that the proximity of stations in these formats in Figure 2 is an artifact of constraining the artists and stations to be located in a 2-dimensional space and that in a space with more dimensions the differences between these formats would be obvious. However, the Measure 1 distances between stations in these formats show a similar pattern and stations can only be close together based on Measure 1 if they play exactly the same artists. The average Measure 1 distance between a pair of stations in the same one of these three formats is 0.72 while the average pair distance between stations in different ones of these three formats is only slightly higher at 0.77. The average Measure 1 distance between any pair of AC category stations in any pair of different formats is much higher at 1.120.

[17] In cases where a single radio group owns several different firms which own radio stations I define ownership at the group level. One problem is that for all but a station's most recent transaction BIAfn lists the announcement date of the deal rather than the date on which the transaction was completed. However, the results are not sensitive to assuming that such deals were completed several months after the date listed in the BIAfn database.

$SAME\_MKTOWNER$ is 1 if i and j are home to the same metro-market and have the same owner. The sum of this coefficient and the $SAME\_OWNER$ coefficient measure how much further apart commonly owned stations in an MMC are than separately owned stations in an MMC.

I estimate (4) with and without dummies (fixed effects) for the pair of stations interacted with the music category (hereafter, category-pair dummies). With fixed effects, the ownership coefficients are identified by how pair distances change following changes in common ownership. The results with fixed effects may be different if, for example, radio groups tend to buy stations which already have similar playlists.

Testing the significance of the coefficients is complicated by the fact that the ε_{ijw} residuals may not be independent across category-pair-weeks. There are two different problems. First, if stations play the same music from month to month then a category-pair's residuals will be correlated across weeks. This can be dealt with by clustering the standard errors at the level of the category-pair. Second, a station's location affects the distance between it and every other station in its category so that ε_{ijw} will be correlated with ε_{ikw} and ε_{jlw}. This is a non-standard problem. As I only calculate pair distances within categories, I calculate standard errors clustered at the level of the category. There are seven music categories in the data and, to calculate p-values, I assume that the t-statistic has a t distribution with 6 degrees of freedom (the number of clusters/categories minus 1).[18] Donald and Lang (2001) and Wooldridge (2003) discuss the complications which can arise when the number of clusters is small so Appendix B provides the results of a simulation exercise which confirms that the resulting p-values are approximately correct. A number of robustness checks which do not suffer from this problem also give similar results.

[18] This is the assumption made by STATA in calculating p-values for regressions where the number of clusters is small (see Stata Corp. (2003), Programming Manual, p. 354 and also Rogers (1993)).

3.4 Summary Statistics

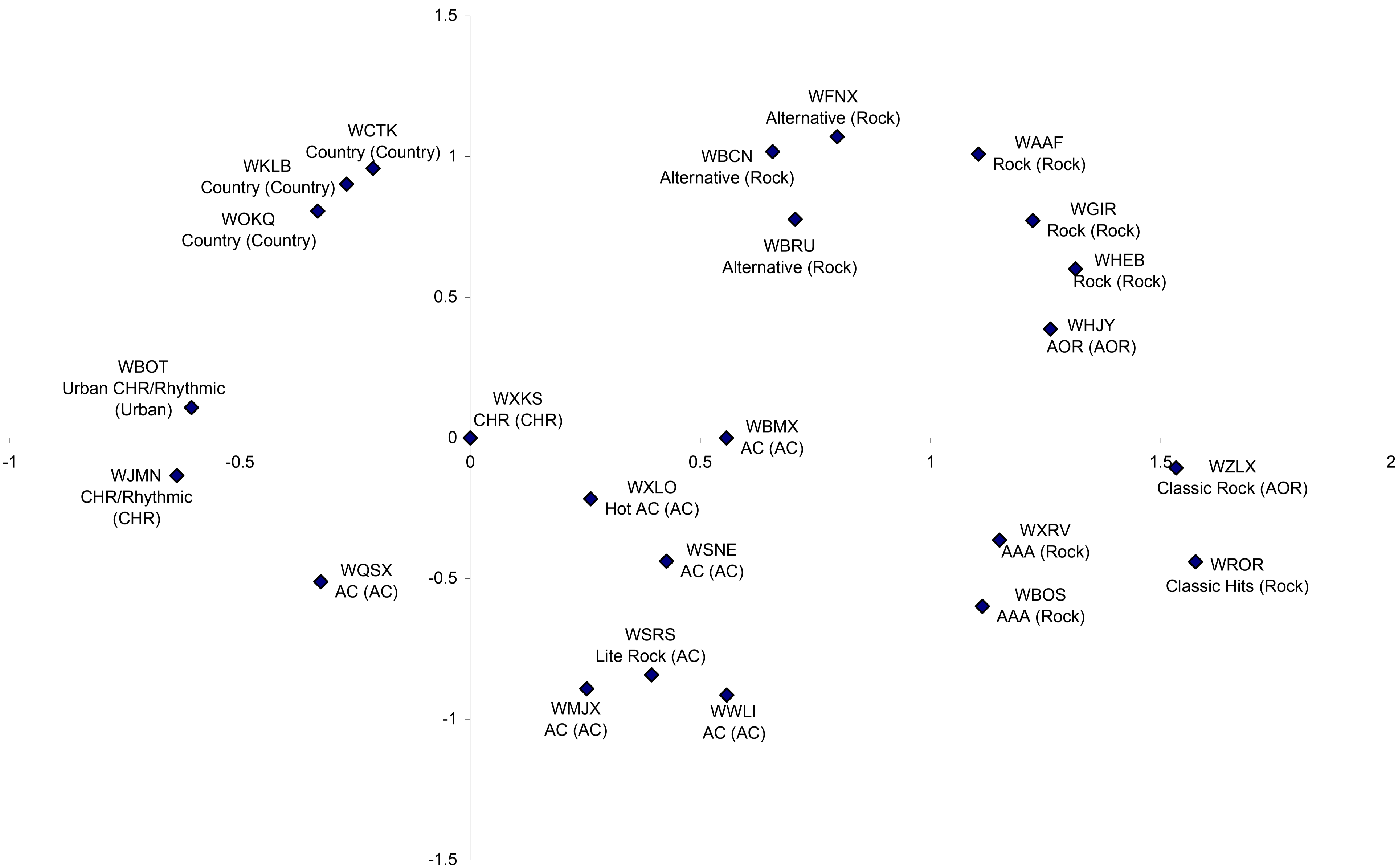
Table 4(a) presents summary statistics on the distance measures. Country stations, which are almost all in the Country format, are closer together, on average, than stations in other categories. A small proportion of station-pairs have no playlist overlap at all so their Measure 1 and 2 distances are $\frac{\pi}{2}$.[19] Some pairs in each category are very close together under Measure 3, but not Measure 1, because they play similar but not identical artists. Pairs which are in the same format as well as the same category (as explained in footnote 15 I define 34 formats for this purpose) are closer together than pairs in different formats, but consistent with the pattern in Figure 2, there is clearly considerable playlist heterogeneity within some formats. To confirm that stations in the same category are more alike than those in different categories, I also calculated the Measure 1 and 2 distances for pairs in *different* categories for November 2001. The averages, 1.484 for Measure 1 and 1.515 for Measure 2, are significantly higher than those for pairs in the same category. Figure 3 illustrates the same point, showing the projection of all stations rated in Boston in November 2001 based on their Measure 1 distances.[20] Stations in the same category are clustered together, although the AOR and Rock categories are not clearly separated. The location of individual stations is also intuitive with, for example, CHR/Rhythmic WJMN close to Urban CHR/Rhythmic WBOT.

Table 4(b) provides summary statistics for the explanatory variables. There are 109,175 distinct category-pairs of stations with an average of 23 observations per pair. 688 distinct pairs are home to the same MMC and 154 of these are commonly owned at some point during the sample. These 154 pairs identify the $SAME\_MKTOWNER$ coefficient without category-pair fixed effects. There are no Oldies pairs in the same MMC. There are 46 changes in whether these pairs are commonly owned, affecting 40 distinct pairs. These 46 changes identify the $SAME\_MKTOWNER$ coefficient with

[19] This is true for less than 1% of pairs, and the regression results are robust to adjusting for censoring of the dependent variable.

[20] The projection procedure is similar to that used to project artists for Measure 3. WXKS is fixed at the origin and WBMX on the x-axis. The figure includes stations which are not home to Boston but which were rated in Boston. WBRU, WHEB and WWLI were not rated in Boston in Fall 2001 but were rated in Boston in other ratings quarters.

Figure 3: Location of Stations Rated in Boston based on their First Week of November 2001 Playlists and Measure 1 (Each Artist Defines a Separate Dimension of Product Space) Pair Distances with Station Formats and (Categories)



fixed effects. The number of pairs which identify the $SAME\_MARKET$ and $SAME\_MKTOWNER$ coefficients is small but the results are still statistically significant and robust. 12,846 distinct pairs from different metro-markets are commonly owned at some point, including some Oldies pairs, and there are 7,385 changes in common ownership. The very large number of pairs for which all of the dummies are zero act as controls, reflected in the category and week dummy coefficients.

3.5 Variety Results

3.5.1 Pair Distance Results: No Category-Pair Dummies

Table 5 columns (1)-(3) report the results of the basic specification without pair dummies for each location measure. The pattern of the coefficients is very similar across the columns suggesting that the way in which station location are defined does not affect the qualitative results.

Stations in the same region have more similar playlists than those in different regions, consistent with some regional variation in tastes for particular artists within categories. Separately owned stations in the same MMC are, on average, significantly more differentiated than randomly-drawn stations in different metro-markets, suggesting that separately owned stations have some incentive to strategically differentiate. The effect is quite large. For example, the Measure 1 $SAME\_MARKET$ coefficient implies that two Adult Contemporary (AC) stations in the same MMC are, on average, 11% further apart than an average AC pair from different markets in the same region. The Measure 3 coefficient implies that they are 27% further apart. On the other hand, stations in different metro-markets tend to be closer together if they are commonly owned. This is consistent with the music research model of Section 2.2. However, the $SAME\_OWNER$ coefficients are only weakly significant and they are relatively small with two AC stations in different markets 4% closer together by Measure 1 (6% Measure 3) if they are commonly owned. This may indicate that tastes are only weakly correlated across markets or that any station can observe other stations' music choices. Stations in the same MMC tend to locate further apart if they are commonly owned. The sums of the

$SAME\_OWNER$ and $SAME\_MKTOWNER$ coefficients are statistically significant at the 1% level for Measures 1 and 3 and at the 5% level for Measure 2. Therefore, even though stations in the same MMC which are separately owned appear to strategically differentiate, common ownership leads to even more differentiation, consistent with the internalization of business stealing being the main effect of common ownership. This is also consistent with Berry and Waldfogel (2001)'s result that within-market common ownership leads to more variety. The effect is large, with the Measure 1 coefficients implying that a pair of AC stations in the same MMC are 10% further apart if the stations are commonly owned (22% Measure 3).

If a common owner of stations in an MMC differentiates them from each other to internalize business stealing, it might move them closer to other stations to steal their listeners. I investigate this by defining a dummy ($ONE\_MKTOWNER$) equal to 1 for separately owned pairs in the same MMC where one or both of the stations in the pair is commonly owned with a different station in the MMC which need not be in the airplay sample. The dummy is 1 at some point during the sample for 296 distinct pairs. If commonly owned stations do move closer to other stations then the coefficient should be negative but in columns (4)-(6) the coefficients are small, statistically insignificant and vary in sign. Commonly owned stations in the same MMC tend to locate further from each other but not systematically closer to other stations.[21]

In columns (7)-(9) I include dummies for the formats of the pair (e.g., a Hot AC-Soft AC dummy equal to 1 if one station is Hot AC and the other is Soft AC). If the coefficients in columns (1)-(3) simply reflect the fact that stations in an MMC, and particularly those which are commonly owned, tend to be in different formats then they should now be statistically insignificant. I also interact the variables with a dummy which is equal to 1 if the stations are in the same format. For example, stations which a common owner describes as being in the same format might be more likely to share

[21]Regressions of the average distance between stations in an MMC on a number of measures of the degree of common ownership confirm that common ownership of some stations increases average variety. I do not report these results to save space.

music research and to add the same songs. The sum of the coefficient on each main variable and its interaction are of similar magnitude to the coefficient in columns (1)-(3). This shows that formats do not capture the differences in station playlists identified in columns (1)-(3). Common ownership of stations in different MMCs only leads to homogenization for stations in the same format. This homogenization is also larger using Measure 2. This is consistent with the music research model because research such as auditorium testing assesses whether particular songs, rather than particular artists or types of music, should be added to playlists. However, while the variety-increasing effects of being in the same MMC or being commonly owned in the same MMC are larger for stations in the same format, the effects are also significant for stations in the same category but different formats.

3.5.2 Pair Distance Results: Category-Pair Fixed Effects

Table 6 gives the results when category-pair dummies are included. I use a large sub-sample of the data because of the large number of dummies. The $SAME\_REGION$ and $SAME\_MARKET$ coefficients are not identified and the ownership coefficients are identified from changes in the distance between pairs following changes in common ownership.

The coefficients in columns (1)-(3) are smaller in absolute magnitude than those in Table 5. The $SAME\_OWNER$ coefficients fall by more proportionally and are not significant at the 10% level even though there are 7,385 changes in whether the stations in different metro-markets are commonly owned. The Measure 1 coefficient implies that a pair of AC category stations in different metro-markets move only 1% closer together when they become commonly owned (Measure 3 2%). The sum of the $SAME\_OWNER$ and $SAME\_MKTOWNER$ coefficients is significant at the 2% level for Measures 1 and 3, although it is not quite significant at the 10% level for Measure 2. The implied increase in differentiation is still relatively large in magnitude: the Measure 1 coefficients imply that a pair of AC stations in the same metro-market move 7% further apart when they become commonly owned (Measure 3 13%). This compares with 10% (Measure 3 22%) from the regressions without category-pair dummies. The smaller effects are consistent with costs, for example from alienating loyal listeners, which cause stations to only change their playlists slowly following ownership changes. The change in the $SAME\_OWNER$ coefficient may indicate that radio groups tend to buy stations in different metro-markets which already play similar music in order to exploit economies of scale and scope in research.

Table 7 illustrates the size of the within-MMC common ownership effect using hypothetical changes to the playlists of two Boston AC stations (WBMX-FM and WMJX-FM). The first part of the table shows how many times each station played 15 of the artists from Figure 1. In November 2001 they played different mixes of artists even though they were both in the Adult Contemporary format. Their playlists overlapped for artists in the middle of Figure 1 like Matchbox Twenty, Enya and Dido. The second part of the table shows playlist changes, keeping the total number of plays on each station the same, which would move the stations further apart by the distance implied by the Measure 1 $SAME\_MKTOWNER$ coefficient (net of the $SAME\_OWNER$ coefficient), with each station playing less of the Enya-type artists and more of its specialist artists. The implied changes are clearly non-trivial. The increase in the Measure 3 distance is only half of the increase implied by the Measure 3 coefficients, even though the playlist changes were designed to draw stations further apart in Measure 3 product space, so the changes implied by the Measure 3 coefficients would be even larger.

Columns (4)-(6) show that when stations in an MMC become commonly owned they do not move closer to stations in the MMC owned by other firms: as in Table 5, the $ONE\_MKTOWNER$ coefficients are all small, insignificant and vary in sign. Columns (7)-(9) includes format-pair dummies and interactions of the ownership variables with a $SAME\_FORMAT$ dummy. The sums of the coefficients on the main effects and interactions are broadly similar to columns (1)-(3) showing that the implied playlist changes are not simply a reflection of changes in station formats. The $SAME\_MKTOWNER$ effect is not larger for stations in the same format than for stations in the same category.[22] Common

[22] As there are only 3 pairs home to same metro-market and the same format which change whether they are commonly owned, this is not surprising.

ownership of stations in different markets has a significant homogenizing effect for stations in the same format when stations are located using Measure 2. However, even in this case, the estimated effect is less than half of the size of the variety-increasing effect of within-MMC common ownership.

3.5.3 Pair Distance Results: Robustness Checks

Table 8 presents six robustness checks on the Measure 1 and Measure 3 regressions in columns (1) and (3) of Tables 5 and 6. The results are qualitatively similar for Measure 2.

Some stations have short weekly playlists (for example, they may have more talk programming) and I am missing daily logs for some station-weeks. Check 1 drops pair-weeks in which either station has less than 1,000 plays, about 45% of pair-week observations. The coefficients remain almost exactly unchanged.

Check 2 treats a pair as being in the same metro-market if there is any metro-market in which both stations are rated rather than if they have the same home market. I now set $SAME\_MARKET$ equal to 1 for 155 category-pairs like WBMX-FM (home to Boston and also rated in Providence, RI) and WSNE-FM (home to Providence and also rated in Boston). 13 of these pairs are also commonly owned at some point during the sample ($SAME\_MKTOWNER$ becomes 1) and all of these pairs change whether they are commonly owned. The $SAME\_MARKET$ and $SAME\_MKTOWNER$ coefficients fall and, with fixed effects, $SAME\_MKTOWNER$ becomes insignificant. This suggests that stations locate based on conditions in their home market which is consistent with the fact that an average of 81% of the audience of a station rated in more than one metro-market comes from its home market as does 68% of the audience of a station rated in at least 5 markets.[23]

Check 3 confirms that my results are not explained by differentiation between stations in a market increasing over time independent of common ownership as suggested by Williams et al. (2002). This

[23] Author's calculation based on Arbitron Average Quarter Hour Persons listening data for Fall 2001 for the stations in the airplay data. The averages for all stations are very similar (79% and 70.3% respectively). Stations should also care more about increasing their home metro-market audience if local advertisers value an additional local listener more than an additional out-of-market listener.

could appear as an ownership effect in my regressions because more stations are commonly owned over time. On the other hand, Williams et al. do not allow for common ownership to increase differentiation only between stations in the same MMC. I therefore include interactions between the week dummies and the $SAME\_MARKET$ dummy. If common ownership does not play a role in increasing differentiation then the $SAME\_MKTOWNER$ coefficient should now be insignificant. Instead, the coefficient is almost unchanged from the original specification, indicating that common ownership does increase differentiation within MMCs.

A station's optimal location could change due to entry and exit by other stations in its MMC. In check 4 I include dummies for the number of stations in the MMC of each station in the pair and an additional set of dummies for the number of stations when both stations are home to the same market. The $SAME\_MARKET$ coefficient is not identified even without category-pair fixed effects. The results show that the ownership coefficients do not simply reflect differences in or changes in the number of stations in an MMC.[24]

A radio executive suggested to me that radio groups share research primarily at the regional level. In check 5 I restrict the sample to pairs in the same region. This also allows me to cluster standard errors at the category-region level giving 61 independent clusters. 1,875 distinct category-pairs in the same region are commonly owned at some point during the sample. The $SAME\_OWNER$ coefficients are larger than before but the differences are not significant.[25]

Check 6 provides further assurance that the dependence between the residuals for different category-pairs does not lead to the significance of the coefficients being exaggerated. I use a very small sub-sample of the data in which each station appears in only one pair in a category. Standard errors are

[24] The results also remain the same in (not reported) regressions where I only use MMCs where there are at least 3 stations. I also estimated the regressions using only stations which are the only stations in their MMC to see if the homogenizing effect of common ownership across markets is larger for stations which did not have to locate themselves relative to a local competitor. The homogenizing effect is only slightly larger, and the difference is not statistically significant.

[25] The larger number of independent clusters tends to make the results more significant. In particular, the variety-increasing effect of within-MMC common ownership under Measure 2 with fixed effects is statistically significant at the 5% level.

clustered on the category-pair to allow for serial correlation in distances across weeks for the same pair. The selection of the sub-sample is described beneath the table and there are only 32 pairs which are home to the same MMC which change whether they are commonly owned. The sums of the $SAME\_OWNER$ and $SAME\_MKTOWNER$ coefficients are significant at the 1% level without fixed effects and at the 2% level with fixed effects.

3.5.4 Alternative Specification: Distance from Center of Category

If two separately owned, symmetric stations locate on the unit interval with a uniform distribution of listeners, it is natural to assume that, in equilibrium, they locate symmetrically around $\frac{1}{2}$. If they become more differentiated when they become commonly owned, we expect them to move further away from $\frac{1}{2}$ as well as from each other. The pair distance specification tests whether commonly owned stations differentiate themselves from each other and I now test whether commonly owned stations also move away from the center of their category, specializing more in a particular kind of music.[26]

The dependent variable is the distance between each station and the center in the category-week. For Measures 1 and 2, the center is defined by the aggregating all of the playlists in the category-week and the distance is the angle between the station location vector and the aggregate playlist location vector. For Measure 3, the center is defined by the average of stations' x– and y-coordinates and the distance is the straight line distance in the plane. The linear specification is

$$y_{iw}^{CENTER} = X_{iw}\beta_1 + C_{iw}\beta_2 + W_w\beta_3 + \varepsilon_{iw} \tag{5}$$

X_{iw} contains $ANOTHER\_IN\_MMC$, a dummy equal to 1 if there are other stations home to i's MMC, and $NUMBER\_OWNED\_IN\_MMC$, a count of the stations i's owner owns in the MMC. These variables are calculated using all stations in the MMC including those which are not in the

[26] Of course, with a more general product space or distribution of listeners it is possible that the internalization of business stealing would lead at least one of the stations to move towards the center of the music category.

airplay sample. C_{iw} and W_w are category and week dummies. Assuming that a station's weekly playlist has a negligible effect on the center of the category, ε_{iw} should be independent across stations which is an additional advantage of this specification. I allow ε_{iw} to be correlated across weeks for a particular station by clustering standard errors at the level of the station.

The results are shown in Table 9. In columns (1)-(3) I do not include station-category fixed effects. A station offers more specialized music when there are other stations in the MMC and when it is commonly owned with more of those stations.[27] This is consistent with the pair distance results. In columns (4)-(6) I include dummies for stations' formats and, consistent with the results in Table 5 columns (7)-(9), the increased specialization is only partially captured by station formats. Columns (7)-(9) include station-category fixed effects. The $ANOTHER\_IN\_MMC$ coefficient is very close to zero. This is not surprising as the number of stations in an MMC is primarily a function of market size which changes little between 1998 and 2001. The ownership effect is smaller with the fixed effects but it is statistically significant at the 5% level for each location measure. The coefficients are also similar in (not reported) regressions where I include dummies for the number of stations in the MMC interacted with category dummies to control for station entry and exit.

4 Does Common Ownership Increase Station Listenership?

I now examine whether changes in common ownership have affected station listenership. If a common owner of stations in an MMC internalizes business stealing then this should tend to increase their total audience. Changes in listenership may also provide some evidence on whether common ownership has tended to increase listener welfare although the relationship between aggregate station listenership and listener welfare need not be monotonic when stations change their playlists.[28]

[27] The distance each station moves from the center of the category is less than half of the distance stations move from each other because stations are not arranged symmetrically around the center.

[28] The welfare of listeners who preferred their old playlists will fall and the welfare of those preferring their new playlists will increase. The change in aggregate welfare depends on the intensity of preferences of the two groups but the change in listenership depends on the elasticity of their time spent listening with respect to what is played. However, aggregate listenership is the best gauge of listener welfare which is available.

Section 4.1 introduces the listenership data. Section 4.2 tests whether the audience of station pairs in the airplay data increases when they become commonly owned. Section 4.3 presents the results from estimating a nested logit model of listenership using a much larger sample of stations and markets.

4.1 Listenership Data

Arbitron collects listener diary data from a large number of metro-markets producing 4 seasonal ratings reports for large markets and 2 (Spring and Fall) for small markets. A commercial station is rated in a report if enough diary-keepers report that they listen to it. I use two share numbers. The first is a station's AQH share of radio listening (including to non-commercial or non-rated stations) in its market. This share is calculated based on listening by individuals aged 12 and above (12+) during an average quarter-hour (AQH) in a broadcast week of Monday-Sunday 6am-12pm. The second number is average proportion (APR) of the 12+ population in the market listening to any radio station during an AQH for the same broadcast week.

I use AQH share data for 281 metro-markets from the Spring and Fall reports for Spring 1996 to Fall 2002 and from the Winter and Summer reports for large markets from 2000 to 2002.[29] The panel of markets is not balanced because more markets are surveyed each year. I also collected APR data for the Spring and Fall surveys from Spring 1996 to Fall 2002 although this data is missing for some individual market-quarters. Appendix C contains more details of the data used in this section. Summary statistics are in Table 10.

4.2 Listenership of Station Pairs in the Airplay Data

I start by examining whether the audience of station-pairs in the same MMC in the airplay data increases when they become commonly owned. I measure their combined audience using the pair's com-

[29] I do not use data from markets which were only surveyed for one year and I also drop all observations from Puerto Rico. Puerto Rico is an unusual market with all of the rated stations broadcasting in the Spanish category and very high radio listenership.

bined share of total radio listening in their home metro-market during the ratings quarter ($SHARE\_LISTENING$) and the average proportion of the 12+ population in the metro-market listening to either station ($SHARE\_12+$). I use these measures in natural logs. There is, at most, one observation per pair per ratings quarter.[30] I only have APR observations for the Spring and Fall surveys so there are, at most, two observations per pair per year for $SHARE\_12+$. Summary statistics are presented in Table 10(a). I only include pairs from the same market and cluster standard errors at the level of the metro-market.

In Table 11 columns (1) and (2) I regress the pair listenership measures on a $SAME\_MKTOWNER$ dummy together with ratings quarter and category dummies. The $SAME\_MKTOWNER$ dummy is the minimum of the $SAME\_MKTOWNER$ dummies defined in Section 3 for the pair during the relevant ratings period, so that if the stations become commonly owned during the ratings period the dummy is 0. The $SAME\_MKTOWNER$ coefficients are positive and significant at the 1% level and the column (1) coefficient implies that commonly owned pairs have, on average, an 11.5% greater combined share of radio listening than separately owned pairs. However, this could be because radio groups tend to buy stations with larger listenerships.

In columns (3) and (4) I include category-pair dummies so that the ownership effect is identified from changes in listenership following 35 changes in whether pairs are commonly owned.[31] Stations which become commonly owned increase their combined audience but the effect is only statistically significant at the 10% level in column (4). This coefficient implies that audiences increase by 3.3% when a pair becomes commonly owned. It is also larger than the column (3) coefficient which is consistent with some of the audience increase coming from increased listenership to radio. The lack of statistical significance is not surprising given the small number of relevant ownership changes and the

[30] An airplay observation from the first weeks of April-June counts for the Spring quarter, July-September for the Summer quarter, October-December for the Fall quarter and January-March for the Winter quarter. If I have no airplay observation for the relevant period then there is no pair-quarter observation for that pair.

[31] There are fewer pair ownership changes than in Section 3 because for some pairs I do not have airplay data during the Spring and Fall ratings periods for 1998 and 1999 and for some other pairs the stations become commonly owned in one ratings period and cease to be commonly owned in the next rating period so that the $SAME\_MKTOWNER$ dummy is 0 for both of these periods.

fact that the quarterly data gives a maximum of 12 observations per pair. The pairs therefore provide some weak evidence that common ownership of stations in an MMC increases their listenership, as well as variety, consistent with the internalization of business stealing.[32]

4.3 Nested Logit Model of Station Listenership

I now estimate a discrete choice, nested logit model of station listenership using data from all categories including non-music categories such as News and Talk. A nested logit model defines an algebraic relationship between the mean utility of a product, its market share, the combined market share of various groups of products (nests) and the proportion of potential consumers not choosing any of the products.[33] The strong functional form assumption controls for changes in the quality or number of other products. An increase in a product's share, relative to the shares of the nests and of the outside good (not listening), implies an increase in that product's mean utility. I use the nested logit model as a convenient way to examine how changes in station ownership affect its listenership, the listenership of its category and aggregate radio listening.

Figure 4 shows the nesting structure. I assume that stations in the same category are closer substitutes than those in different categories, and that stations in different categories are closer substitutes with each other than with the outside good. The market is defined as the hours of people aged 12 and above in an Arbitron metro-market during the broadcast week. A person consumes the outside good when they do not listen to a commercial radio station with a non-zero share in Arbitron's report.[34]

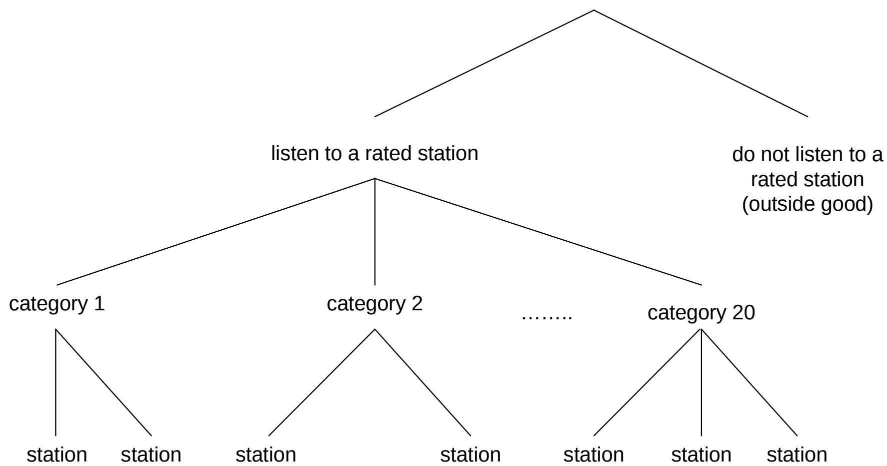
The mean utility of station s in category c_s in metro-market m is a linear function of observed station characteristics (X_{sm}), such as ownership or transmitter power, market characteristics which affect the attractiveness of the category ($X_{c_s m}$), such as being a Country station in the South, observed market characteristics (X_m) which affect the attractiveness of listening to the radio, such as average

[32] The $SAME\_MKTOWNER$ coefficients remain positive, but are statisitcally insignificant, when dummies for the number of stations in the MMC and dummies for the identity of the stations in the MMC are included.

[33] Berry (1994), Greene (1997, p. 865-871) and Nevo (2000) provide additional discussion of the nested logit model.

[34] Berry and Waldfogel (1999a) use the same definition.

Figure 4: Nesting Structure for the Nested Logit Model of Station Listenership



commuting times, and the effect of unobserved characteristics (ξ_{sm}), such as DJ ability.

Normalizing the mean utility of the outside good to zero, the share of station s in market m in ratings quarter t (s_{smt}) is

$$s_{smt} = \frac{e^{X_{smt}\beta_1+\xi_{smt}}}{\sum_{r\epsilon c_s mt} e^{X_{rmt}\beta_1+\xi_{rmt}}} \frac{e^{X_{c_smt}\beta_2+\tau I^{c_s}_{mt}}}{\sum_{c=1}^{C} e^{X_{cmt}\beta_2+\tau I^{c}_{mt}}} \frac{e^{X_{mt}\beta_3+\delta I^{in}_{mt}}}{1+e^{X_{mt}\beta_3+\delta I^{in}_{mt}}} \quad (6)$$

$$\text{where } I^{c}_{mt} = \ln\left(\sum_{r\epsilon c_s mt} e^{X_{rmt}\beta_1+\xi_{rmt}}\right) \text{ and } I^{in}_{mt} = \ln\left(\sum_{c=1}^{C} e^{X_{c_mt}\beta_2+\tau I^{c}_{mt}}\right) \quad (7)$$

The βs, δ and τ are parameters and the Is are "inclusive value" variables reflecting the utilities of stations in lower branches of the nesting structure.[35] As in Berry (1994), (6) can be rearranged to give a linear estimating equation

$$\ln s_{smt} - \ln s_{omt} = (1-\delta)\ln(s_{in,csmt}) + (1-\delta\tau)\ln(s_{c,smt}) + X_{smt}\beta_1\tau\delta + X_{c_smt}\beta_2\delta + X_{mt}\beta_3 + \tau\delta\xi_{smt} \quad (8)$$

where s_{omt} is the share of the outside good, $s_{c,smt}$ is s's share of listening to stations in its MMC and $s_{in,csmt}$ is s's MMC's share of rated commercial radio listening. For the nesting structure to be

[35]In (6) and (7) C is the number of categories and $r\epsilon c_s mt$ is a station in the same category as s in market m in quarter t.

consistent with utility maximization δ and τ must lie in the unit interval (McFadden (1981), p. 230), implying that the $\ln(s_{c,smt})$ coefficient should be larger than the $\ln(s_{in,csmt})$ coefficient with both of them in the unit interval. The unobserved ξ_{smt} will be correlated with $s_{c,smt}$ and $s_{in,csmt}$. If s's unobserved characteristics are uncorrelated with the observed characteristics of other stations then these characteristics can be used as instruments for $\ln(s_{c,smt})$ and $\ln(s_{in,csmt})$.[36] Radio groups tend to buy relatively large stations so it is necessary to use station fixed effects to identify the effect of ownership changes. To be precise, I use station-market-category fixed effects so that a station's quality can be different in different metro-markets in which it is rated and its quality can change if it switches to a new category.

When I include fixed effects stations in different categories appear to be better substitutes. There is a simple reason for this. Controlling for differences such as the popularity of Country music in the South, the total listenership of different categories is fairly similar across metro-markets and varies relatively little with the exact number of stations in each category or the distribution of market shares across the stations. In a nested logit model this cross-sectional pattern is explained by the categories being poor substitutes for each other.[37] On the other hand, with fixed effects substitution patterns are identified only by changes in listenership when stations enter, exit or change category. The data records smaller stations as switching categories quite frequently but many of these switches may involve only small changes in airplay (for example, from Classic Hits in the Rock category to Classic Rock in the AOR/Classic Rock category) in which case a station may take most of its listeners to its new category. In a nested logit model this pattern implies that categories are good substitutes for each other. These different substitution patterns give different predictions for what should happen if two stations within an MMC merge and their quality increases, holding everything else constant. If categories are assumed

[36] If stations choose their category based on other stations' unobserved characteristics then the instruments will be invalid. I experimented with only using instruments which are more clearly exogenous such as population and the characteristics of out of market stations. However, these produced substitution patterns in some specifications which were not consistent with utility maximization.

[37] Low substitution between formats is also found by Berry and Waldfogel (1999a) using data from a cross-section (see especially their Table 6 p. 416).

to be good substitutes then a large proportion number of additional listeners should come from other categories and the outside good. If this assumption is incorrect and few additional listeners come from outside of their category then the model will explain this by common ownership having only a small effect on quality.

I present two different sets of estimates. When I estimate (8) including fixed effects the results imply that categories are relatively good substitutes and the implied effect of common ownership within an MMC is positive but small and not statistically significant. I also estimate substitution patterns from a cross-section and then, in a second step, estimate the effects of common ownership assuming that these substitution patterns are correct. These estimates imply that common ownership within an MMC leads to quite large and statistically significant increases in listenership. In both sets of estimates, common ownership of stations in different metro-markets has a very small and statistically insignificant effect on listenership.

4.3.1 Data Sample and Variable Definitions

I use data from the Spring and Fall Arbitron surveys from 1996 to 2002 from 281 metro-markets, giving 94,770 station-market-quarter observations. I define three ownership variables based on the transaction history in the BIAfn database.

DUM_OWNER_MMC is a dummy equal to 1 if the station is commonly owned with another station rated in its MMC. Neither station need be home to the metro-market. If common ownership of stations in an MMC increases listenership then this coefficient should be positive.

DUM_OWNER_MKT is a dummy equal to 1 if the station is commonly owned with another station rated in its metro-market. Neither station need be home to the metro-market. The coefficient will reflect any ownership effects which are not category-specific and so are less likely to be related to product variety.

$OWNER\_CATEGORY$ is the number of different stations an owner has in the category across all rated metro-markets. The coefficient should be positive if cross-market common ownership increases station listenership. I use the natural log of this variable because any effect is unlikely to be linear.

Table 10(b) presents summary statistics. There are 5,298 changes in ownership for the stations in the sample and the average values of $OWNER\_CATEGORY$, DUM_OWNER_MKT and DUM_OWNER_MMC increase from 2.5, 0.60 and 0.140 respectively in Spring 1996 to 26.6, 0.78 and 0.269 in Fall 2002.

Stations might increase their listenership by improving technical characteristics, such as transmitter power. Observed technical characteristics are listed in Table 10(b). Unfortunately, I only have technical characteristic data for Fall 2001, and the effect of fixed technical characteristics cannot be identified separately from the coefficients on station-market-category fixed effects. If common owners tend to improve stations' technical characteristics then this effect will be reflected in the coefficients on the ownership variables. I also only have data on market characteristics such as average commuting times for Fall 2001. However, these market characteristics, which could affect aggregate radio listening, are unlikely to change significantly from Spring 1996 to Fall 2002.

The sum of the station characteristics listed in Table 10(b) for other stations in station s's MMC and other stations in s's metro-market are instruments for $\ln(s_{c,smt})$ and $\ln(s_{in,csmt})$.[38] A few stations have missing data for characteristics such as transmitter power so I also include, as additional characteristics, dummies indicating whether the station has a particular characteristic missing.

4.3.2 Results with Substitution Patterns Estimated from Within Market Entry and Exit

Table 12(a) presents the results of estimating (8) with station-market-category dummies (fixed effects) and ratings quarter dummies. In column (1) the $\ln(s_{c,smt})$ and $\ln(s_{in,csmt})$ coefficients are consistent with utility maximization. Common ownership of stations in the same category but different metro-markets implies an increase in station mean utility but the effect is insignificant. Common ownership

[38] Note that I am using Fall 2001 station characteristics to form instruments for $\ln(s_{c,smt})$ and $\ln(s_{in,csmt})$ in other ratings quarters. These vary over time as other stations enter, exit or switch categories.

of stations in the same metro-market but different categories has a positive and significant effect on mean utility, but common ownership of stations in the same MMC has a smaller and statistically insignificant positive effect.[39]

Two hypothetical within-MMC ownership changes in Boston in Fall 2001 illustrate the implied substitution patterns. The first example involves the only two Urban stations in the market, WBOT-FM and WILD-AM, both owned by Radio One which owned no other Boston stations. If they were sold to separate independents, so that both DUM_OWNER_MKT and DUM_OWNER_MMC become zero, the coefficients imply that each station's audience would fall by 2.2%, with 69% of these listeners switching to the 34 rated stations in other categories and the remainder lost to any rated station. The second example involves the Rock category which has 8 stations. Greater Media owned WBOS-FM and WROR-FM and some non-Rock stations. If Greater Media sold WBOS to an independent but kept WROR then WBOS's audience would fall by 2.0% and WROR's audience would increase by 0.8% as its implied mean utility increases as it remains commonly owned with non-Rock stations. 15% of the net reduction in listeners would switch to the 6 other Rock stations, 56% would switch to stations in other categories and the remaining 29% would be lost to any rated station. Thus, even with several other stations in the category, the substitution patterns imply that a fall in station quality causes more listeners to stop listening to rated stations than switch to stations with very similar programming.

Column (2) allows different effects for the airplay sample, for which we know that within-MMC common ownership increases variety. There are 6,772 station-quarters and 14,447 station-market-quarters from the airplay data as many stations in the airplay data are rated in multiple markets. Common ownership within a metro-market has positive and significantly larger effects for the airplay stations, but the effects are not larger for stations in the same MMC.

[39]When two stations in the same MMC are commonly owned, DUM_OWNER_MKT and DUM_OWNER_MMC are both equal to 1 so the effect is the sum of the coefficients.

4.3.3 Results with Substitution Patterns Estimated from Fall 2001 Cross-Section

Table 12(b) presents the results of estimating (8) using data from Fall 2001, the quarter for which I have accurate station technical characteristic and market characteristic data. The estimated substitution patterns are very similar if I use market share data from other quarters. I do not include station-market-category fixed effects, so the effects of market characteristics, such as demographics and region dummies, station characteristics and category characteristics are identified. I include a full set of interactions between category dummies and market characteristics to allow, for example, Spanish stations to be more popular in markets with a large Hispanic population. The instruments, the sums of characteristics of other stations in the metro-market and in the MMC, are the same as before. The $\ln(s_{in,csmt})$ and $\ln(s_{c,smt})$ coefficients are consistent with utility maximization, are precisely estimated and imply less substitution between categories than the estimates in Table 12(a). The coefficients on characteristics also make intuitive sense with more radio listening in markets with higher commuting times and to stations with more powerful transmitters.

I use the estimated $(1-\delta)$ and $(1-\delta\tau)$ to calculate $\ln s_{smt} - \ln s_{omt} - (1-\delta)\ln(s_{in,csmt}) - (1-\delta\tau)\ln(s_{c,smt})$ for each station-market-quarter. I regress this new variable on the ownership variables, station-market-category dummies and ratings quarter dummies. The results are shown in Table 12(c). Common ownership of stations in the same metro-market and category has a positive and significantly larger effect on mean utility than common ownership of stations in the same metro-market but different categories. Common ownership of stations in the same category in different metro-markets has a very small, insignificant and negative effect on mean utility. The effects for the airplay sub-sample are not significantly different to the effects for the rest of the sample.

The size of the within-MMC effects and the substitution patterns can be seen by repeating the two hypothetical ownership changes. The coefficients imply that the sale of Urban stations WBOT-FM and WILD-AM to separate independents would result in each station losing 7% of its listeners, with

87% going to the 34 rated stations in other categories and the remainder lost to rated stations. The sale of WBOS by the owner of WROR and some non-Rock stations would result in WBOS's audience falling by 11.6% and WROR's falling by 7.8%. 43% of the lost listeners would go to the 6 other Rock stations, 49% to rated stations in other categories and 8% would stop listening to rated stations. The falls in listenership are larger with the cross-sectional substitution patters and, when there are several category competitors, a reduction in station quality results in more listeners switching to similar stations than stop listening to rated stations.

4.3.4 Is it Variety which Increases Listenership?

These results provide some evidence that when stations in the same market become commonly owned their audiences increase. However, this might happen because a characteristic which affects absolute station quality changes rather than because horizontal product differentiation increases. For example, the common owner might hire better DJs or play fewer commercials to exercise market power in the advertising market. While listeners might like fewer commercials, it would reduce the welfare of advertisers.

If product differentiation increases listenership then common ownership should have larger effects for stations in the same category. The nested logit results using cross-sectional substitution patterns suggest that this might be the case. I now present the results of a test, using the fact that some stations are rated in multiple markets, which provides further evidence that these results are more consistent with listenership increasing due to product differentiation (variety explanation) than a reduction in advertising (market power explanation) or an increase in some other aspect of quality.

A simple example illustrates the logic of the test. Assume that a station's differentiation or advertising decisions are based only on considerations in its home MMC.[40] Suppose that two stations, A and B, have the same home MMC (metro 1), that they become commonly owned and that their

[40] The result of robustness check 2 in Section 3.5.3 provides some evidence that differentiation is affected by common ownership only in a station's home market.

owner owns no other stations. In addition, A is rated in metro 2 but B is not. First, suppose that common ownership leads to fewer commercials. All else equal, this should increase the quality of each station for listeners and their audience in any market in which either station is rated. For example, A's audience in metro 2 should increase when it has fewer commercials because of common ownership in metro 1. Second, suppose that A and B do not change the number of commercials but move apart in product space to internalize business stealing. All else equal, this should increase their audience in metro 1. However, it is not clear that A's audience should increase in metro 2 because A's new location does not internalize business stealing with any station in that market. Depending on the location of other stations in metro 2 A's audience could increase, decrease or stay the same. I therefore test whether common ownership of a station in its home MMC increases its listenership in markets in which all of its commonly owned home MMC sister stations are absent. If so, the data is consistent with the market power explanation. If not, the data is inconsistent with the market power explanation but consistent with the variety explanation.

I define two new dummies. DUM_OWNER_ATHOME equals 1 if the station is commonly owned in its home MMC with another station home to the same MMC. $DUM\_OWNER\_SAMEHOME$ equals 1 if the station is rated in the MMC along with another station which has the same owner and the same home metro-market.[41] The coefficient on DUM_OWNER_MMC now measures any effect associated with two rated stations having the same owner when they are not home to the same market and they are not commonly owned in their home MMCs. If a station's location and advertising decisions are only affected by conditions in its home market then this coefficient should be insignificant. The market power explanation predicts that the DUM_OWNER_ATHOME coefficient will be positive and the $DUM\_OWNER\_SAMEHOME$ will be insignificant. The variety explanation predicts the opposite pattern.[42]

[41] In the example above, DUM_OWNER_ATHOME would be 1 for A in metro 1 and metro 2, and 1 for B in metro 1. $DUM\_OWNER\_SAMEHOME$ would be 1 for A and B in metro 1 but 0 for A in metro 2.

[42] There are 1,188 station-market-category quarters where one of the new dummies changes value and the other does not, allowing their effects to be separately identified.

Table 13(a) column (1) presents the results when I take substitution patterns from the Fall 2001 cross-section and do not allow for different effects for stations in the airplay sample. The coefficient on $DUM\_OWNER\_SAMEHOME$ is positive and significant and the DUM_OWNER_ATHOME coefficient is very close to zero. Stations which become commonly owned in their home MMC do not, on average, increase their listenership in markets where their home market sister stations are absent. This is true even if there is another station with the same owner but from a different home market (Table 13(b) test 1). On the other hand, if a home MMC sister station is present then a station does tend to increase its listenership (test 2). This pattern is consistent with the variety explanation but not the market power explanation. The DUM_OWNER_MMC coefficient is insignificant, consistent with a station basing its playlist decisions on conditions in its home market.

Column (2) presents the results distinguishing the airplay sample, for which I know common ownership in the same MMC increases variety, from other stations. There are so many coefficients reflecting MMC ownership that most of them are individually insignificant, but the tests listed below the table show that the same pattern holds for both groups of stations: common ownership increases listenership only in the presence of home market sister stations.

5 Conclusion

This paper provides evidence that a common owner of music radio stations with the same home metro-market and in the same music category increases the degree of product differentiation between these stations. Based on a number of measures of station location, the effect on variety is quite large and robust. The paper also provides evidence that when stations with the same home metro-market become commonly owned they tend to increase their listenership. While the conclusions on listenership are less robust and the size of the effects varies across specifications, in none of the results does common ownership appear to reduce station audiences. The variety and listenership results are consistent with the internalization of business stealing being the main effect of common ownership. The paper also shows that common ownership of stations in different metro-markets results in, at most, a very small homogenization of playlists with no effect on station listenership.

Three issues deserve further comment. The first issue is whether we should have a preference for the listenership estimates which use substitution patterns estimated from the cross-section. These results imply that common ownership within an MMC has a large, positive and highly significant effect on station listenership and that increased variety provides a good explanation for increases in listenership. The substitution patterns estimated from the cross-section are more intuitively plausible; in particular, it seems highly unlikely that a decline in station quality would lead more listeners to stop listening to commercial stations than would switch to stations offering similar programming. However, the implied effects of ownership on listenership are much larger than I find using very simple regressions on the listenership of station pairs from the airplay sample. It seems plausible that the size of the effects results, in part, from the functional form assumptions of the nested logit model. One very clear direction for future work is to combine the audience and variety data in a single framework to understand the relationship between listenership and station locations more clearly.

The second issue is whether it matters that I do not use an instrument for changes in station ownership. The danger is that something unobserved could cause changes in station ownership, location and listenership which I will misinterpret as a causal effect of ownership changes. This possibility cannot be ruled out completely. However, it is hard to imagine what factor, other than the preceding ownership change, would lead an Adult Contemporary station to start playing less of Enya and more of Celine Dion which is the kind of change I observe in the data. I also note that increased differentiation of playlists to avoid business stealing is consistent with comments made by station programmers of commonly owned stations (see, for example, footnote 5). Finally, most of the station ownership changes which I observe result from the purchase of one radio group owning multiple stations by another group. This makes it unlikely that an ownership change for an individual station would be correlated with something which would also make it change location.

The third issue is whether there are unambiguous conclusions for listener welfare or for policy on multiple station ownership. It is not necessarily the case that an increase in station audiences has to be associated with an increase in listener welfare, partly because there is no price mechanism which can take into account differences in the intensity of listeners' preferences. However, the results are consistent with common owners of music radio stations in a market increasing product differentiation in order to try to better serve a greater number of listeners. This suggests that ownership consolidation to date has been beneficial to listeners. A complete analysis of social welfare would also have to take into account the effects of consolidation on advertisers and the ability of radio groups to exploit economies of scale and scope to reduce costs. Ownership consolidation in contemporary music categories, the focus of this paper, may also be more desirable than consolidation in news or talk categories because important issues associated with news coverage and viewpoint diversity are less relevant.

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A Projection of Artists into the 2-Dimensional Plane

This Appendix describes how I project artists into a 2-dimensional plane to calculate stations' Measure 3 locations. The procedure used to locate the large number of artists in a category-week is:

1. locate artists in a high dimensional space where each station in the category is an orthogonal dimension and an artist's location reflects the share of its plays coming from each station. For example, if there are three stations and an artist is played 15, 5 and 0 times on stations X,Y and Z respectively then the artist's location vector would be $(\frac{3}{4}, \frac{1}{4}, 0)$;

2. measure the pairwise distances between each of the 30 most played artists in the category in the high dimensional space, measuring the distance by the angle (in radians) between the location vectors;

3. locate these artists in the plane by minimizing (3) with respect to the artists' x- and y-coordinates. The distances d_{ij} are the high-dimensional space distances between each pair of artists calculated in step 2. The most played artist is fixed at the origin and the second most played on the x-axis. The minimization uses a non-linear least squares routine (lsqnonlin) in MATLAB. (3) may have multiple local minima, so I start the minimization at 11 different sets of starting values and use the estimates which give the lowest final value of the objective function. The first set places all artists at the origin and the other sets are formed by drawing the x- and y-coordinates from an independent, bivariate standard normal distribution; and,

4. measure the distance between the 31^{st} most played artist and each of the 30 most played artists in the high dimensional space, and then locate the 31^{st} most played artist by minimizing (3) taking the locations of the 30 most played artists as given. A single starting point, at the average coordinates of the artists already located, is used. This procedure is then repeated for each subsequent artist, taking the location of all previous artists as given.

A station is located at the weighted average coordinates of the artists where the weights are the share of each artist the station's playlist. The distances between stations and the distribution of artists are quite robust to placing up to 50 artists simultaneously and using up to 1,300 different starting points in step 3. For example, using 1,300 different starting points the only significant change in Figure 1 is that Madonna is placed between Dido and John Mellancamp, close to the 80s Hits stations.

B Standard Errors in the Pair Distance Regressions

This Appendix describes a simulation exercise which checks that the p-values reported in Tables 5, 6 and 8 are approximately correct. The potential problem is that the residuals may not be independent across pairs of stations because the location of a station affects any pair of which it is a member. I use the distance between pairs in the same music category and cluster the standard errors at the category level, assuming that t-statistics are distributed t with degrees of freedom equal to the number of categories minus 1. Donald and Lang (2001) and Wooldridge (2003) discuss the complications which can arise when the number of clusters is small so it is necessary to confirm that the reported p-values are not misleading.

B.1 Simulation Exercise

The exercise is designed to preserve the structure of the correlations in the actual data. In each repetition, each station keeps its actual characteristics (home market, music category, ownership history) but it is randomly assigned, without replacement, the locations of another station in its category in every week. Random assignment implies that there should be no systematic relationship between pair characteristics and pair distances. I repeat the basic Measure 1 and Measure 3 regressions and calculate whether the estimated coefficients are statistically significant at the 1, 5 or 10% levels given the assumed distribution of the t-statistics. I use 500 repetitions. If the distribution of the standard errors is correct then I expect, for example, to reject the null hypothesis that a coefficient is zero at the 5% level in 5% of the repetitions.

I perform the exercise with and without category-pair dummies. It is not feasible to use the entire sample. Without category-pair dummies, I use data from 2001 for the 807 stations with data in every week. The regressions correspond to columns (1) and (3) in Table 5. With category pair dummies, I need a significant number of ownership changes in the data, so I use stations with at least 35 weeks of data and use the data from every fourth month from July 1998 to November 2001. I also drop the smallest category, Oldies. The regressions correspond to columns (1) and (3) in Table 6.

B.2 Results

Tables A1 (a)-(d) report the results. The first column in each table reports the estimates using the sub-sample of actual data used in the exercise. The rejection rates are close to the nominal size of the test for each coefficient and each distance measure, although they appear to be slightly too high for the regressions without category-pair dummies. For example, the null hypothesis that the $SAME\_MKTOWNER$ coefficient is zero is rejected at the 10% significance level in 11.8% of the repetitions. However, the $SAME\_MKTOWNER$ coefficients are significant at the 1% level in Table 5.

C Data used in the analysis of listenership

This Appendix describes the data used in Section 4. The major sources are the Fall 2001 version of BIAfn's *Media Access Pro* database (BIAfn) with updates for Fall 2002 and issues of *Duncan's American Radio* (Duncan) from Spring 1996 to Spring 2001 when it ceased publication.

C.1 Arbitron ratings

C.1.1 Station shares of radio listening (AQH 12+)

The primary source of data is BIAfn with Duncan used to fill in shares for 20 stations which exited in earlier years and stations with gaps in their recorded share data which are mainly Canadian and Mexican stations rated in US markets. BIAfn does not include in a station's share the shares of other stations which "simulcast" its signal in the same market. However, these shares are typically small.

C.1.2 Total radio station listening (APR 12+)

APR ratings for Spring 1996 to Spring 2001 are taken from Duncan and for Fall 2001 to Fall 2002 they are derived from data in M Street's STAR database which gives the average number of people listening to each station and the market population as well as each station's AQH share. Both sources contain a small number of missing market-quarters, especially for small markets, and these market-quarters are dropped. I am unable to control for changes in Arbitron market boundaries over time but Arbitron's website states that boundaries are "relatively static" and are primarily changed following the decennial census.

C.2 Station Categories

BIAfn provides quarterly station format data which was supplemented by Duncan for exiting stations and in cases where BIAfn data was missing. Formats were categorized into 19 BIAfn categories (listed in Table 10(c)) using BIAfn's Fall 2001 classification. It was straightforward to include Duncan's formats in this classification. 231 station-quarters (mainly for Canadian and Mexican stations) have missing format information in both BIAfn and Duncan. These were grouped into an "Unknown" category.

C.3 Station Characteristics

Data on the station characteristics listed in Table 10(b) come from the Fall 2001 version of BIAfn except the home metro-market and band (AM or FM) for stations which exit the market which come from Duncan. BIAfn contains some missing data for characteristics such as transmitter power.

C.4 Metro-Market Characteristics

Data on the metro-market demographic and region characteristics listed in Table 10(b) come from the Fall 2001 version of BIAfn apart from average commuting times which come from Arbitron's website and are derived from the 2000 census. Income is the average gross income less taxes per capita. I classify markets into the 9 geographic regions used by BIAfn (East North Central, East South Central, Mid Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central and West South Central).

C.5 Station Ownership

BIAfn gives a transaction history for each station which lists the buyer, seller and announcement date (month-year) and whether the deal was completed for each proposed transaction. The closing date is given for the most recent completed transaction for each station and I use this date for the last transaction and the announcement dates for earlier transactions. Owners of the exiting stations are identified from Duncan and none of them were traded before exiting. There are 4 issues with the ownership data. First, an owner's name can be listed differently for different stations and I have tried to make sure that (only) stations owned by the same firm are identified as such by checking the names of directors, notes included in the transaction history and transaction records at the front of Duncan publications. In cases where ownership was still unclear I treated the stations as independents. Second, for 5% of stations the parent company is listed as different from the owner. There is no transaction history for parents but the results are not sensitive to replacing the current owner with the current parent. Third, almost no transactions are recorded for Canadian and Mexican stations. It is not clear whether this is correct. The results are not sensitive to dropping markets where Canadian or Mexican stations are rated. Finally, my treatment of ownership ignores LMAs where one station sells commercial time for another station without owning it. LMAs may or may not influence other aspects of programming.

Table 1: Categories and Formats

Category	Number of Formats in Category	Formats in Category with more than 5 Stations	Number of Stations in Format
Adult Contemporary (AC)	24	Adult Contemporary	268
		Hot AC	135
		Soft AC	80
		80s Hits	45
		Modern AC	31
		Soft Rock	29
		Lite AC	23
		Lite Rock	16
		Soft Hits	8
		Mix AC	5
Album Oriented Rock/ Classic Rock (AOR)	5	Classic Rock	257
		AOR	93
		AOR/Classic Rock	9
Contemporary Hit Radio/ Top 40 (CHR)	21	CHR	233
		Top 40	52
		CHR/Rhythmic	24
		Adult CHR	11
		CHR/Dance	9
		Rhythmic/Oldies	9
		CHR/Top 40	6
		Rhythmic/CHR	5
Country	6	Country	638
Oldies	14	Oldies	330
Rock	17	Rock	111
		Alternative	80
		Classic Hits	60
		Modern Rock	48
		AAA	30
		Adult Rock	9
		Rock AC	9
		New Rock	8
Urban	26	Urban	105
		Urban AC	91
		R&B Oldies	28
		Rhythm/Blue	13
		Urban/Gospel	9
		Urban/Oldies	8
		Urban CHR	7

Note: based on all stations rated (i.e., non-zero share of radio listenership) by Arbitron in Fall 2001 in 281 metro-markets. The seven categories are those used in the analysis of music variety.

Table 2: Coverage of the Airplay Sample
Based on Fall 2001 Categories and Station Ratings

Category	Number of Metro-Market Categories (MMCs) with Home to MMC Stations in the Airplay Sample	Number of Home to MMC Rated Stations	Number of Home to MMC Stations in Airplay Sample	Average % of Listening to Home to MMC Stations Accounted for by the Airplay Sample
Arbitron Metro-Markets Ranked 1-70 (1 is New York City and 70 is Ft. Myers, FL)				
Adult Contemporary (AC)	66	221	162	89.2
Album Oriented Rock/Classic Rock (AOR)	65	111	98	95.9
Contemporary Hit Radio/Top 40 (CHR)	64	131	112	95.6
Country	64	141	94	92.1
Oldies	44	64	44	92.1
Rock	61	147	122	94.0
Urban	44	133	88	86.0
Arbitron Metro-Markets Ranked 71 and above (71 is Knoxville, TN)				
Adult Contemporary (AC)	56	135	78	78.7
Album Oriented Rock/Classic Rock (AOR)	34	66	45	82.5
Contemporary Hit Radio/Top 40 (CHR)	59	96	75	91.4
Country	60	137	76	85.7
Oldies	1	3	1	40.7
Rock	42	80	60	87.5
Urban	27	59	39	85.9

Notes:
Arbitron markets are ranked by population. To understand how to read the table consider the example of the Country music category in the largest 70 Arbitron metro-markets. In 64 of these 70 metro-markets I have airplay data on at least one 1 station which was home to the metro-market and in the Country music category in Fall 2001. There were 141 home to the metro-market Country music stations with non-zero listening shares in these 64 metro-markets and I have airplay data on 94 of these stations. The 94 airplay stations, on average, accounted for 92.1% of the rated listening to Country music stations in their metro-markets.

Table 3: Summary Statistics on the Structure of the Airplay Panel

Year	Number of Stations in Airplay Sample	Number of Station-Weeks	Number of Days in Year	Proportion of Days Missing in Station-Week
1998	702	4,972	40	0.06
1999	886	8,506	19	0.01
2000	953	10,549	60	0.08
2001	1095	11,723	59	0.11

Notes:
To understand how to read the table consider the example of the year 2000. I have airplay data on 10,549 station-weeks during 2000 from 953 different stations. Daily logs in 2000 come from 60 different days (for this year I have every day from the first five weekdays of each month). A certain proportion of days (8% on average) are missing from each station-week.

Table 4: Variety Analysis Summary Statistics

(a) Distance Measures

	Number of station-pair weeks	DISTANCE MEASURE 1 Each Artist Separate Dimension				DISTANCE MEASURE 2 Each Artist-Song Separate Dimension				DISTANCE MEASURE 3 Stations Located in 2-Dimensional Space			
		Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Pairs Distances by Category													
Adult Contemporary (AC)	783,320	1.078	0.314	0.134	1.571	1.247	0.225	0.112	1.571	0.645	0.424	0.000	1.940
Album Oriented Rock/Classic Rock (AOR)	270,579	0.993	0.312	0.292	1.571	1.295	0.191	0.555	1.571	0.631	0.398	0.001	1.891
Contemporary Hit Radio (CHR)	425,893	1.023	0.279	0.317	1.571	1.104	0.260	0.387	1.571	0.562	0.384	0.001	1.881
Country	425,485	0.514	0.212	0.165	1.571	0.870	0.205	0.349	1.571	0.136	0.251	0.000	1.886
Oldies	13,502	0.881	0.432	0.230	1.571	1.170	0.281	0.411	1.571	0.499	0.526	0.001	2.460
Rock	361,947	1.143	0.314	0.248	1.571	1.278	0.239	0.408	1.571	0.779	0.444	0.001	2.055
Urban	175,753	1.068	0.276	0.235	1.571	1.175	0.242	0.283	1.571	0.601	0.394	0.001	1.926
Pairs in Same Format and Category													
Adult Contemporary (AC)	196,223	0.953	0.291	0.134	1.571	1.156	0.214	0.112	1.571	0.467	0.366	0.000	1.868
Album Oriented Rock/Classic Rock (AOR)	136,462	0.851	0.256	0.292	1.571	1.201	0.175	0.555	1.571	0.438	0.310	0.001	1.891
Contemporary Hit Radio (CHR)	269,761	1.006	0.267	0.317	1.571	1.088	0.252	0.387	1.571	0.543	0.369	0.001	1.808
Country	425,485	0.514	0.212	0.165	1.571	0.870	0.205	0.349	1.571	0.136	0.251	0.000	1.886
Oldies	11,101	0.755	0.367	0.230	1.571	1.091	0.246	0.410	1.571	0.356	0.456	0.001	2.460
Rock	86,580	0.908	0.269	0.248	1.571	1.123	0.217	0.422	1.571	0.450	0.327	0.001	1.721
Urban	65,912	0.972	0.247	0.235	1.571	1.094	0.219	0.283	1.571	0.466	0.336	0.001	1.722
Distances from Category Center	**Number of station-weeks**												
(all categories)	35,750	0.720	0.280	0.160	1.568	0.894	0.246	0.304	1.569	0.420	0.270	0.000	1.693

(b) Explanatory Variables

		Type	Mean	Std Dev	Min	Max
Pair Distances	**Number of pairs**					
SAME_REGION	2,456,479	Dummy	0.1289	-	0	1
SAME_MARKET	2,456,479	Dummy	0.0064	-	0	1
SAME_OWNER	2,456,479	Dummy	0.0999	-	0	1
SAME_MKTOWNER	2,456,479	Dummy	0.0015	-	0	1
Distances from Category Center	**Number of station-weeks**					
ANOTHER_IN_MMC	35,750	Dummy	0.824	-	0	1
NUMBER_OWNED_IN_MMC	35,750	Number	1.371	0.603	1	4

Note: Number of observations listed for Measures 1 and 2. There are fewer observations for Measure 3 because 5 station-week observations are dropped because their playlists do not contain any artist played more than 10 times in the category-week

Table 5: Variety Results: Pair Distance Regressions with No Category-Pair Dummies

	(1) Measure 1 Artist Dimensions	(2) Measure 2 Artist-Song Dimensions	(3) Measure 3 Artists in 2D Space	(4) Measure 1 Artist Dimensions	(5) Measure 2 Artist-Song Dimensions	(6) Measure 3 Artists in 2D Space	(7) Measure 1 Artist Dimensions	(8) Measure 2 Artist-Song Dimensions	(9) Measure 3 Artists in 2D Space
SAME_REGION	-0.021 (0.007)	-0.017 (0.006)	-0.019 (0.012)	-0.021 (0.007)	-0.017 (0.006)	-0.019 (0.011)	-0.010 (0.003)	-0.008 (0.003)	-0.005 (0.005)
	[0.032]	[0.039]	[0.171]	[0.032]	[0.039]	[0.171]	[0.020]	[0.034]	[0.339]
SAME_MARKET	0.141 (0.016)	0.102 (0.013)	0.196 (0.026)	0.135 (0.019)	0.094 (0.014)	0.199 (0.025)	0.078 (0.010)	0.050 (0.007)	0.123 (0.015)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
SAME_OWNER	-0.038 (0.016)	-0.032 (0.017)	-0.041 (0.021)	-0.038 (0.016)	-0.032 (0.017)	-0.041 (0.021)	-0.010 (0.014)	-0.003 (0.010)	-0.008 (0.020)
	[0.051]	[0.106]	[0.098]	[0.051]	[0.106]	[0.098]	[0.530]	[0.775]	[0.696]
SAME_MKTOWNER	0.163 (0.029)	0.098 (0.023)	0.222 (0.037)	0.169 (0.029)	0.106 (0.020)	0.219 (0.034)	0.081 (0.023)	0.041 (0.008)	0.096 (0.028)
	[0.001]	[0.005]	[0.001]	[0.001]	[0.002]	[0.001]	[0.014]	[0.002]	[0.014]
ONE_MKTOWNER	-	-	-	0.012 (0.021)	0.016 (0.018)	-0.006 (0.024)	-	-	-
				[0.579]	[0.376]	[0.821]			
<u>Interactions with</u> <u>*SAME_FORMAT*</u>									
SAME_REGION	-	-	-	-	-	-	-0.012 (0.010)	-0.011 (0.010)	-0.013 (0.018)
							[0.272]	[0.324]	[0.510]
SAME_MARKET	-	-	-	-	-	-	0.053 (0.025)	0.043 (0.017)	0.040 (0.033)
							[0.081]	[0.044]	[0.270]
SAME_OWNER	-	-	-	-	-	-	-0.040 (0.012)	-0.045 (0.008)	-0.045 (0.019)
							[0.016]	[0.001]	[0.058]
SAME_MKTOWNER	-	-	-	-	-	-	0.079 (0.093)	0.053 (0.075)	0.134 (0.123)
							[0.430]	[0.508]	[0.318]
Dummies	Week Category	Week Category	Week Category	Week Category	Week Category	Week Category	Week Format of Pair	Week Format of Pair	Week Format of Pair
Adjusted R^2 (includes dummies)	0.3588	0.3383	0.2156	0.3588	0.3383	0.2156	0.5369	0.5003	0.4435
Number of observations	2,456,479	2,456,479	2,456,145	2,456,479	2,456,479	2,456,145	2,456,479	2,456,479	2,456,145

<u>Notes:</u> Standard errors in parentheses robust to heteroskedasticity and clustered at the music category level; p-values in square brackets calculated assuming t-statistics are distributed t with degrees of freedom equal to the number of categories minus 1.

Table 6: Variety Results: Pair Distance Regressions with Category-Pair Dummies (Fixed Effects)

	(1) Measure 1 Artist Dimensions	(2) Measure 2 Artist-Song Dimensions	(3) Measure 3 Artists in 2D Space	(4) Measure 1 Artist Dimensions	(5) Measure 2 Artist-Song Dimensions	(6) Measure 3 Artists in 2D Space	(7) Measure 1 Artist Dimensions	(8) Measure 2 Artist-Song Dimensions	(9) Measure 3 Artists in 2D Space
SAME_OWNER	-0.010 (0.007)	-0.011 (0.006)	-0.011 (0.006)	-0.010 (0.007)	-0.011 (0.006)	-0.011 (0.006)	-0.004 (0.004)	0.001 (0.004)	-0.009 (0.003)
	[0.188]	[0.122]	[0.135]	[0.188]	[0.121]	[0.135]	[0.263]	[0.775]	[0.034]
SAME_MKTOWNER	0.097 (0.028)	0.064 (0.032)	0.119 (0.033)	0.096 (0.029)	0.070 (0.035)	0.125 (0.032)	0.083 (0.022)	0.059 (0.030)	0.122 (0.040)
	[0.013]	[0.091]	[0.011]	[0.018]	[0.093]	[0.008]	[0.010]	[0.099]	[0.021]
ONE_MKTOWNER	-	-	-	-0.002 (0.019)	0.011 (0.022)	0.012 (0.022)	-	-	-
				[0.937]	[0.639]	[0.614]			
Interactions with *SAME_FORMAT*									
SAME_OWNER	-	-	-	-	-	-	-0.012 (0.013)	-0.025 (0.004)	-0.007 (0.008)
							[0.379]	[0.001]	[0.462]
SAME_MKTOWNER	-	-	-	-	-	-	0.024 (0.034)	-0.000 (0.037)	-0.015 (0.038)
							[0.506]	[0.992]	[0.703]
Dummies	Week Category-Pair	Week Category-Pair	Week Category-Pair	Week Category-Pair	Week Category-Pair	Week Category-Pair	Week Category-Pair Format of Pair	Week Category-Pair Format of Pair	Week Category-Pair Format of Pair
Adjusted R^2 (includes dummies)	0.9317	0.8955	0.9315	0.9317	0.8955	0.9315	0.9308	0.8955	0.9295
Number of observations	1,548,039	1,548,039	1,547,823	1,548,039	1,548,039	1,547,823	801,751	801,751	801,606
Number of changes in *SAME_OWNER*	7,385	7,385	7,385	7,385	7,385	7,385	7,385	7,385	7,385
Number of changes in *SAME_MKTOWNER*	46	46	46	46	46	46	46	46	46

Notes:
1. Standard errors in parentheses robust to heteroskedasticity and clustered at the music category level; p-values in square brackets calculated assuming t-statistics are distributed t with degrees of freedom equal to the number of categories minus 1.
2. Regressions use a sample of category-pair distances. Sample for columns (1)-(6) contains all category-pairs which are in the same region or are ever commonly owned plus a 50% random sample of the remaining pairs. Sample for columns (7)-(9) contains all category-pairs which are in the same region or are ever commonly owned plus a 10% random sample of other pairs.

Table 7: Example Illustrating how Playlist Changes Affect Station Locations and Pair Distances

Actual Playlists in First Week of November 2001				
	WMJX-FM		WBMX-FM	
Total Number of Plays in Week	1389		1344	
Celine Dion	20		0	
Faith Hill	21		0	
Billy Joel	23		0	
Elton John	39		5	
Rod Stewart	39		0	
Lifehouse	0		34	
Train	0		23	
Dave Matthews	0		44	
Staind	0		33	
U2	1		65	
Dido	19		17	
Enya	20		40	
Jewel	14		15	
Matchbox Twenty	19		14	
Uncle Kracker	15		14	
Measure 3 coordinates (in Figure 2)	(-0.135,-0.149)		(-0.419,-1.160)	
Pair Distance: Measure 1		1.332		
Pair Distance: Measure 3		1.050		
Hypothetical Alternative Playlists				
	WMJX-FM		WBMX-FM	
Total Number of Plays in Week	1389		1344	
Celine Dion	39	(+ 19)	0	
Faith Hill	35	(+ 14)	0	
Billy Joel	43	(+ 20)	0	
Elton John	39		5	
Rod Stewart	39		0	
Lifehouse	0		47	(+ 13)
Train	0		37	(+ 14)
Dave Matthews	0		44	
Staind	0		33	
U2	1		65	
Dido	19		4	(- 13)
Enya	0	(- 20)	40	
Jewel	0	(- 14)	15	
Matchbox Twenty	0	(- 19)	14	
Uncle Kracker	15		0	(- 14)
Measure 3 coordinates	(-0.125,-0.110)		(-0.424,-1.174)	
Pair Distance: Measure 1		1.419 (+ 0.087)		
Pair Distance: Measure 3		1.105 (+ 0.055)		

Table 8: Variety Results: Pair Distance Regressions Robustness Checks

(a) Regressions with No Category-Pair Dummies

	Measure 1: Each Artist as a Dimension of Product Space				Measure 3: Artists and Stations in 2D Product Space			
	SAME_REGION	*SAME_MARKET*	*SAME_OWNER*	*SAME_MKTOWNER*	*SAME_REGION*	*SAME_MARKET*	*SAME_OWNER*	*SAME_MKTOWNER*
Original coefficients	-0.021 (0.007) [0.032]	0.141 (0.016) [0.000]	-0.038 (0.016) [0.051]	0.163 (0.029) [0.001]	-0.019 (0.012) [0.171]	0.196 (0.026) [0.000]	-0.041 (0.021) [0.098]	0.222 (0.037) [0.001]
Robustness Check								
1. Use only pair-weeks where each station has at least 1,000 plays	-0.021 (0.008) [0.036]	0.133 (0.021) [0.001]	-0.036 (0.015) [0.057]	0.178 (0.030) [0.001]	-0.019 (0.013) [0.179]	0.178 (0.029) [0.001]	-0.041 (0.022) [0.105]	0.240 (0.036) [0.001]
2. *SAME_MARKET=1* if stations both have listening in any market	-0.014 (0.007) [0.071]	0.025 (0.011) [0.058]	-0.036 (0.016) [0.063]	0.115 (0.023) [0.003]	-0.010 (0.011) [0.378]	0.044 (0.018) [0.045]	-0.039 (0.021) [0.119]	0.150 (0.047) [0.018]
3. Week dummies interacted with *SAME_MARKET* dummy	-0.021 (0.007) [0.032]	-	-0.038 (0.016) [0.051]	0.164 (0.029) [0.001]	-0.019 (0.012) [0.171]	-	-0.041 (0.021) [0.099]	0.222 (0.037) [0.001]
4. Include dummies for the number of stations in each MMC	-0.023 (0.008) [0.027]	-	-0.059 (0.020) [0.025]	0.184 (0.017) [0.000]	-0.023 (0.012) [0.104]		-0.065 (0.024) [0.037]	0.245 (0.026) [0.000]
5. Use only pairs from the same region	-	0.142 (0.009) [0.000]	-0.048 (0.012) [0.000]	0.173 (0.019) [0.000]	-	0.198 (0.014) [0.000]	-0.046 (0.013) [0.001]	0.223 (0.026) [0.000]
6. Each station appears in only one category-pair	-0.015 (0.049) [0.764]	0.178 (0.051) [0.001]	-0.033 (0.026) [0.214]	0.183 (0.039) [0.000]	0.004 (0.056) [0.943]	0.247 (0.060) [0.000]	-0.030 (0.032) [0.353]	0.236 (0.051) [0.000]

(b) Regressions with Category-Pair Dummies (Fixed Effects)

	Measure 1: Each Artist as a Dimension of Product Space				Measure 3: Artists and Stations in 2D Product Space			
	SAME_REGION	*SAME_MARKET*	*SAME_OWNER*	*SAME_MKTOWNER*	*SAME_REGION*	*SAME_MARKET*	*SAME_OWNER*	*SAME_MKTOWNER*
Original coefficients	-	-	-0.010 (0.007) [0.188]	0.097 (0.028) [0.013]	-	-	-0.011 (0.006) [0.135]	0.119 (0.033) [0.011]
Robustness Check								
1. Use only pair-weeks where each station has at least 1,000 plays	-	-	-0.006 (0.005) [0.305]	0.117 (0.024) [0.003]	-	-	-0.005 (0.005) [0.310]	0.131 (0.025) [0.002]
2. *SAME_MARKET=1* if stations both have listening in any market	-	-	-0.010 (0.007) [0.197]	0.020 (0.018) [0.308]	-	-	-0.011 (0.006) [0.142]	0.031 (0.028) [0.297]
3.Week dummies interacted with *SAME_MARKET* dummy	-	-	-0.010 (0.007) [0.190]	0.092 (0.026) [0.012]	-	-	-0.011 (0.006) [0.137]	0.115 (0.032) [0.011]
4. Include dummies for the number of stations in each MMC	-	-	-0.010 (0.007) [0.183]	0.098 (0.028) [0.012]	-	-	-0.011 (0.007) [0.140]	0.121 (0.032) [0.010]
5. Use only pairs from the same region	-	-	-0.014 (0.006) [0.026]	0.101 (0.024) [0.000]	-	-	-0.010 (0.006) [0.138]	0.117 (0.034) [0.000]
6. Each station appears in only one category-pair	-	-	-0.013 (0.012) [0.295]	0.103 (0.033) [0.002]	-	-	-0.007 (0.014) [0.580]	0.109 (0.042) [0.010]

Notes: 1. Checks 1-4: standard errors in parentheses robust to heteroskedasticity and clustered at the music category level; p-values in square brackets calculated assuming t-statistics are distributed t with degrees o freedom equal to the number of independent clusters minus 1. Standard errors for check 5 clustered at the category-region level.
2. Check 6 uses a sub-sample of the data with each station appearing in only one pair in a category, which gives 13,040 observations. The sub-sample was selected by the following procedure. First, take the category-pairs which are home to the same MMC and change whether they are commonly owned. If a station appears in multiple pairs, randomly select a single pair to keep for the sub-sample. Then take the category pairs which are home to the same MMC and are always commonly owned, drop any pair with a station already in the sub-sample and randomly select pairs where stations appear in multiple pairs in this group. Repeat this procedure for pairs home to the same MMC which are never commonly owned, pairs home to different MMCs which change whether they are commonly owned, pairs home to different MMCs which are always commonly owned and, finally, all remaining pairs. Standard errors are clustered on the category-pair and t-statistics are assumed to be distributed asymptotically normal.

Table 9: Variety Results: Station Distance from Center of Category

	(1) Measure 1 Each Artist as a Dimension	(2) Measure 2 Each Artist-Song as a Dimension	(3) Measure 3 Artists in 2D space	(4) Measure 1 Each Artist as a Dimension	(5) Measure 2 Each Artist-Song as a Dimension	(6) Measure 3 Artists in 2D space	(7) Measure 1 Each Artist as a Dimension	(8) Measure 2 Each Artist-Song as a Dimension	(9) Measure 3 Artists in 2D space
ANOTHER_IN_MMC	0.087 (0.014)***	0.068 (0.013) ***	0.085 (0.014)***	0.068 (0.011)***	0.058 (0.010)***	0.069 (0.012)***	-0.009 (0.006)	-0.004 (0.006)	0.001 (0.006)
NUMBER_OWNED_IN_MMC	0.031 (0.010)***	0.018 (0.009) **	0.033 (0.010)***	0.024 (0.008)***	0.015 (0.007)**	0.026 (0.009)***	0.014 (0.007) **	0.014 (0.007) **	0.014 (0.007) **
Dummies	Category Week	Category Week	Category Week	Format Week	Format Week	Format Week	Station-Category Week	Station-Category Week	Station-Category Week
Adjusted R^2 (includes dummies)	0.4019	0.3512	0.3646	0.5658	0.5417	0.4942	0.9236	0.8953	0.9225
Number of observations	35,750	35,750	35,745	35,750	35,750	35,745	35,750	35,750	35,745

Note: Standard errors in parentheses robust to heteroskedasticity and clustered on the station. ***,** and * denote significance at the 1, 5 and10% levels respectively.

Table 10: Listenership Analysis Summary Statistics

(a) Listenership of Airplay Sample Pairs in the Same Metro-Market Category

	Number of pair-quarters	Mean	Standard Deviation	Min	Max
SHARE_LISTENING	4,714	0.090	0.031	0.018	0.247
SHARE_12+	3,014	0.014	0.004	0.003	0.040
SAME_MKTOWNER (dummy)	4,714	0.230	-	0	1

(b) Nested Logit Model of Station Listenership

	Number of station-market-quarters	Mean	Standard Deviation	Min	Max
Listenership Shares					
s_{smt}	94,770	0.005	0.005	0.000	0.058
s_{omt}	94,770	0.870	0.015	0.799	0.935
$s_{c,smt}$	94,770	0.439	0.345	0.003	1
$s_{in,csmt}$	94,770	0.121	0.089	0.001	0.743
Ownership Variables					
DUM_OWNER_MKT (dummy)	94,770	0.721	-	0	1
DUM_OWNER_MMC (dummy)	94,770	0.223	-	0	1
OWNER_CATEGORY (station count)	94,770	14.059	27.070	1	144
Station Characteristics (Fall 2001 only)	**station-markets**				
AGE (years plus 1)	7,075	40	20	2	94
AM_DAYMW (AM daytime transmitter power, kW/1000)	1,858	0.016	0.020	0.000	0.100
AM_NIGHTMW (AM nighttime transmitter power, kW/1000)	1,720	0.013	0.020	0.000	0.150
FM (dummy, 1 if station FM)	7,095	0.738	-	0	1
FM_HAAT (FM transmitter height, feet/1000)	5,230	0.908	0.905	-0.289	48.632
FM_MW (FM transmitter power, kw/1000)	5,235	0.043	0.041	0.000	0.320
OUT_AM (dummy, 1 if station AM and not home to market)	7,095	0.066	-	0	1
OUT_METRO (dummy, 1 if station not home to market)	7,095	0.351	-	0	1
Metro-Market Characteristics (Fall 2001 only)	**markets**				
INCOME ($000 per capita post tax)	281	17.683	3.593	8.845	36.436
ASIAN (proportion)	281	0.028	0.048	0.004	0.674
BLACK (proportion)	281	0.113	0.106	0.003	0.517
HISPANIC (proportion)	281	0.093	0.136	0.005	0.943
POP_OVER65 (proportion aged over 65)	281	0.127	0.033	0.036	0.332
POP_UNDER18 (proportion aged under 18)	281	0.257	0.029	0.171	0.373
POP_18TO24 (proportion aged 18 to 24)	281	0.098	0.030	0.048	0.284
COMMUTETIME (average commute time in minutes)	281	22.711	3.851	15.100	38.300

Notes: Market characteristics statistics based on one observation per market. Station characteristics based on one observation per station-market. FM_HAAT and FM_MW only calculated for FM stations, and AM_DAYMW and AM_NIGHTMW for AM stations.

(c) Number of Station-Market-Quarters in Each Category for Nested Logit Model

Categories	Station-market-quarters	Categories	Station-market-quarters
Adult Contemporary (AC)	12,927	News	8,740
Album Oriented Rock/Classic Rock (AOR)	8,037	Nostalgia/Big Band	3,445
Classical	836	Oldies	7,193
Contemporary Hit Radio/Top 40 (CHR)	7,550	Religion	5,422
Country	12,698	Rock	7,602
Easy Listening/Beautiful Music	612	Spanish	4,814
Ethnic	193	Sports	2,978
Jazz/New Age	1,513	Talk	2,505
Middle of the Road	930	Unknown	231
Miscellaneous	540	Urban	6,004

Table 11: Listenership of Airplay Sample Pairs in the Same Metro-Market Category (MMC)

Dependent Variable	(1) Pair *LN(SHARE_LISTENING)*	(2) Pair *LN(SHARE_12+)*	(3) Pair *LN(SHARE_LISTENING)*	(4) Pair *LN(SHARE_12+)*
SAME_MKTOWNER	0.1151 (0.0322)***	0.1108 (0.0618)***	0.0272 (0.0172)	0.0334 (0.0175)*
Dummies	Ratings Quarter Category	Ratings Quarter Category	Ratings Quarter Category-Pair	Ratings Quarter Category-Pair
Adjusted R^2 (includes dummies)	0.2015	0.2294	0.9200	0.9093
Number of observations	4,714	3,014	4,714	3,014

Note: standard errors in parentheses robust to heteroskedasticity and clustered at the metro-market level. ***, ** and * indicate significance at the 1,5 and 10% levels respectively.

Table 12: Nested Logit Model of Listenership

(a) Substitution Patterns Estimated from Within-Market Variation

	(1)	(2)
$\ln(s_{in,csmt})$, $1-\delta$	0.6540 (0.0265)***	0.6523 (0.0266)***
$\ln(s_{c,smt})$, $1-\delta\tau$	0.6859 (0.0240)***	0.6844 (0.0242)***
DUM_OWNER_MKT	0.0081 (0.0030)***	0.0068 (0.0030)**
LN(OWNER_MKT)	-	-
DUM_OWNER_MMC	-0.0026 (0.0029)	-0.0029 (0.0031)
LN(OWNER_CATEGORY)	0.0007 (0.0010)	0.0007 (0.0011)
*AIRPLAY * DUM_OWNER_MKT*	-	0.0121 (0.0037)***
*AIRPLAY * DUM_OWNER_MMC*	-	0.0004 (0.0037)
*AIRPLAY * LN(OWNER_CATEGORY)*	-	-0.0012 (0.0011)
Dummies	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category
Number of observations	94,770	94,770

(c) Substitution Patterns Estimated from Fall 2001 Cross-Section (see Table 12(b) for estimates of substitution patterns)

	(1)	(2)
DUM_OWNER_MKT	0.0038 (0.0015)**	0.0035 (0.0016)**
LN(OWNER_MKT)	-	-
DUM_OWNER_MMC	0.0082 (0.0014)***	0.0085 (0.0015) ***
LN(OWNER_CATEGORY)	-0.0003 (0.0005)	-0.0003 (0.0006)
*AIRPLAY * DUM_OWNER_MKT*	-	0.0029 (0.0019)
*AIRPLAY * DUM_OWNER_MMC*	-	-0.0013 (0.0019)
*AIRPLAY * LN(OWNER_CATEGORY)*	-	-0.0002 (0.0006)
Dummies	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category
Number of observations	94,770	94,770

<u>Note</u>

1. Standard errors in parentheses are robust to heteroskedasticity and clustered on the identity of the station
2. ***, ** and * indicate significance at 1,5 and 10% level respectively
3. Table 12(a) uses 2SLS (for instruments see text), 12(c) OLS

Table 12(b): Estimation of Nested Logit Model Substitution Patterns from Fall 2001 Cross-Section

$\ln(s_{in,csmt})$, 1-δ	0.856 (0.009) ***
$\ln(s_{c,smt})$, 1-δτ	0.920 (0.005) ***
Market Characteristics	
INCOME	-0.002 (0.001)
ASIAN	0.294 (0.069) ***
BLACK	0.109 (0.052) **
HISPANIC	0.245 (0.039) ***
POP_OVER65	-0.401 (0.204) **
POP_UNDER18	-0.231 (0.291)
POP_18TO24	-1.841 (0.258) ***
COMMUTETIME	0.007 (0.002) ***
Station Characteristics	
FM	0.075 (0.010) ***
*AM*NEWS_TALK_SPORT*	0.003 (0.016)
LN_AGE	0.018 (0.003) ***
OUT_METRO	-0.113 (0.006) ***
*OUT_METRO*AM*	0.017 (0.009) *
FM_MW	0.435 (0.060) ***
AM_DAYMW	0.632 (0.276) **
AM_NIGHTMW	0.805 (0.302) ***
FM_HAAT	0.006 (0.004)
Dummies	Categories Regions Categories x Market Characteristic Interactions Category x Region Interactions Dummies for Stations lacking Particular Characteristics
Instruments for $\ln(s_{in,csmt})$ and $\ln(s_{c,smt})$	Sum of Station Characteristics for Other Stations in Market-Category Sum of Station Characteristics for Stations in Other Categories in the same Metro-Market
Number of observations	7,095

Notes
1. Standard errors in parentheses, robust to heteroskedasticity and clustered on the identity of the station.
2. ***, ** and * indicate significance at 1,5 and 10% levels respectively

Table 13: Does Product Differentiation Cause Listenership to Increase?

(a) Coefficient Estimates

	(1)		(2) Separate Effects for AIRPLAY Sample Station-Quarters	
LN(OWNER_CATEGORY)	-0.0002 (0.0005)		-0.0003 (0.0006)	
DUM_OWNER_MKT	0.0037 (0.0015)	**	0.0034 (0.0015)	**
*AIRPLAY*LN(OWNER_CATEGORY)*	-		-0.0000 (0.0006)	
*AIRPLAY*DUM_OWNER_MKT*	-		0.0027 (0.0019)	
MMC Effects				
DUM_OWNER_MMC	0.0028 (0.0022)		0.0036 (0.0025)	
*AIRPLAY*DUM_OWNER_MMC*	-		-0.0029 (0.0032)	
DUM_OWNER_ATHOME	0.0001 (0.0032)		0.0018 (0.0034)	
*AIRPLAY*DUM_OWNER_ATHOME*	-		-0.0062 (0.0042)	
DUM_OWNER_SAMEHOME	0.0076 (0.0037)	**	0.0052 (0.0039)	
*AIRPLAY*DUM_OWNER_SAMEHOME*	-		0.0083 (0.0051)	*
Number of observations	94,770		94,770	

Note
1. Standard errors in parentheses are robust to heteroskedasiticty and clustered on the identity of the station
2. All regressions contain quarter and station-market-category dummies
3. Dependent variable defined in text, calculated using substitution patterns from Table 12(b)
4. ***, ** and * indicate significance at 1,5 and 10% levels respectively

(b) Significance Tests on Linear Combinations of Coefficients

	F-test statistic	**P-value**
Tests based on results in column (1):		
(1) DUM_OWNER_MMC + DUM_OWNER_ATHOME = 0	F(1,80632)=0.62	0.4300
(2) DUM_OWNER_MMC + DUM_OWNER_ATHOME + DUM_OWNER_SAMEHOME = 0	F(1,80632)=37.96	0.0000
Tests based on results in column (2):		
(3) DUM_OWNER_MMC + DUM_OWNER_ATHOME = 0	F(1,80627)=1.80	0.1801
(4) DUM_OWNER_MMC + DUM_OWNER_ATHOME + DUM_OWNER_SAMEHOME = 0	F(1,80627)=35.35	0.0000
(5) *DUM_OWNER_SAMEHOME + AIRPLAY*DUM_OWNER_SAMEHOME* = 0	F(1,80627)=7.18	0.0074
*(6) DUM_OWNER_MMC + AIRPLAY*DUM_OWNER_MMC + DUM_OWNER_ATHOME + AIRPLAY*DUM_OWNER_ATHOME* = 0	F(1,80627)=0.53	0.4669
*(7) DUM_OWNER_MMC + AIRPLAY*DUM_OWNER_MMC + DUM_OWN_ATHOME + AIRPLAY*DUM_OWN_ATHOME+ DUM_OWNER_SAMEHOME + AIRPLAY*DUM_OWNER_SAMEHOME* =0	F(1,80627)=17.81	0.0000

Table A1: Results of Monte Carlo Simulation Exercise

(a) Measure 1 without Category-Pair Dummies

	Coefficients, (Standard Errors) and [P-values] using Sub-Sample of Actual Data	Simulation % Rejection Rates of the Null Hypothesis Using Conventional Asymptotic Critical Values		
		10%	5%	1%
SAME_REGION	-0.027 (0.007) [0.011]	11.4	7.2	2.2
SAME_MARKET	0.157 (0.026) [0.001]	12.8	5.2	1.4
SAME_OWNER	-0.040 (0.025) [0.157]	11.4	6.2	1.2
SAME_MKTOWNER	0.173 (0.037) [0.003]	11.8	7.0	2.2
Dummies	Week, Category			
Number of observations	665,028			

(b) Measure 3 without Category-Pair Dummies

	Coefficients, (Standard Errors) and [P-values] using Sub-Sample of Actual Data	Simulation % Rejection Rates of the Null Hypothesis Using Conventional Asymptotic Critical Values		
		10%	5%	1%
SAME_REGION	-0.026 (0.011) [0.058]	13.6	6.8	1.8
SAME_MARKET	0.206 (0.038) [0.002]	12.6	6.0	1.6
SAME_OWNER	-0.048 (0.031) [0.177]	11.5	6.4	0.6
SAME_MKTOWNER	0.242 (0.041) [0.001]	12.0	7.4	1.8
Dummies	Week, Category			
Number of observations	665,028			

Notes:
Critical values for the t-statistic (distributed t with 6 dof) for 10, 5 and 1% tests are 1.943, 2.447 and 3.708 respectively. Each table uses 500 simulations.

(c) Measure 1 with Category-Pair Dummies

	Coefficients, (Standard Errors) and [P-values] using Actual Data	Simulation % Rejection Rates of the Null Hypothesis Using Conventional Asymptotic Critical Values		
		10%	5%	1%
SAME_OWNER	-0.009 (0.007) [0.262]	9.0	3.8	0.4
SAME_MKTOWNER	0.088 (0.030) [0.030]	11.0	5.8	1.4
Dummies	Week, Category-Pair			
Number of observations	277,335			

(d) Measure 3 with Category-Pair Dummies

	Coefficients, (Standard Errors) and [P-values] using Actual Data	Simulation % Rejection Rates of the Null Hypothesis Using Conventional Asymptotic Critical Values		
		10%	5%	1%
SAME_OWNER	-0.012 (0.007) [0.007]	9.0	4.2	0.6
SAME_MKTOWNER	0.090 (0.032) [0.036]	6.8	2.8	0.2
Dummies	Week, Category-Pair			
Number of observations	277,335			

Notes:
Critical values for the t-statistic (distributed t with 5 dof) for 10, 5 and 1% tests are 2.015, 2.571 and 4.032 respectively. Each table uses 500 simulations.