The Effects of Horizontal Mergers on Product Positioning: Evidence from the Music Radio Industry

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December 14, 2008

Abstract

Standard merger analysis in differentiated product industries assumes that the merging parties do not change how their products are positioned. This paper uses rich station-level data from the music radio industry to show that there are significant programming changes after mergers. In particular, common owners differentiate their stations from each other, but also make them more like stations owned by competitors. Consistent with these changes in positioning, and in a way which is not explained by changes in commercial loads (prices), listeners are redistributed from competitors to the merging parties. The observed changes mean that mergers may have quite different effects from those envisaged in the *Horizontal Merger Guidelines*.

*E-mail: atsweet@duke.edu. I thank Glenn Ellison, Paul Joskow, Jerry Hausman, Whitney Newey, Nancy Rose, Aviv Nevo, Brent Goldfarb, Greg Crawford, Simon Anderson, Alan Sorenson, Charles Romeo, Joel Waldfogel, Stephen Coate and seminar participants at several schools, the NBER Summer Institute and the FTC for useful comments. Stephen Finger, Daniel Szoke and Jake Zahniser-Word provided excellent research assistance. This paper has had a number of previous titles including the "Too Much Rock and Roll? Station Ownership, Programming and Listenership". I thank Rich Meyer of Mediabase 24/7 for providing access to the airplay data and the National Association of Broadcasters (NAB) for funding the purchase of BIAfn's Media Access Pro database. All views and any errors in this paper are my own.

1 Introduction

Standard merger analysis in differentiated product markets, as summarized in the *Horizontal Merger Guidelines* (US Department of Justice and Federal Trade Commission (1997)), asks whether a merger will raise prices assuming that the products offered by the merging parties will not change. Repositioning by competitors is considered only to the extent that the threat of repositioning may constrain the merging parties from raising prices. The limited consideration given to repositioning stems partly from a lack of general theoretical predictions about how multiproduct firms position their products, but also from a lack of empirical evidence showing that post-merger repositioning is important.

The main contribution of this paper is to show that horizontal product repositioning after mergers can be important, in ways which the standard approach to mergers does not even consider, using data from the commercial music radio industry. I show that when the owners of stations in the same music category merge, their stations tend to become more differentiated from each other, while also becoming more like stations which are owned by competitors. Consistent with common owners doing this to take listeners from other stations, while reducing audience cannibalization by their own stations, listeners are redistributed from competitors to the merging parties. There is also some evidence that this increased competitive pressure induces some competitors to move to different music categories i.e., away from the merging parties. Thus repositioning seems to be used as a competitive tool by the merging parties to increase their market share, a possibility which is ignored in the *Guidelines*. Furthermore these changes happen quite quickly - within one year after a merger - which is within the time frame typically considered in merger analysis. At the same time there are no significant changes in prices (here, the number of commercials which stations play per hour).

There are several reasons why the music radio industry is a good place to study the effects of mergers on horizontal positioning.[1] First, one can make use of high quality and high frequency data on the music content of programming (playlists) to study location decisions, together with listenership

[1] I am unable to look at vertical aspects of programming such as the quality of the DJs. Spectrum constraints prevent station owners from increasing the quality of stations' signals in most markets.

data to measure quantities. The playlist data also provides information on the number of commercials played. Second, there was rapid ownership consolidation in the late 1990s and early 2000s providing a relatively large number of mergers (and also demergers) to examine. Furthermore, some of the ownership changes involved combinations of stations in many formats and markets so that they are likely to exogenous to ongoing changes in programming for individual stations. Third, there are no technological or regulatory barriers to stations changing their programming content following a change in ownership. As a result, I observe the changes in positioning happening quite quickly following mergers, which makes it easier to attribute the changes in positioning to the changes in ownership. Finally, there has been a real policy debate about how concentration in the radio industry has affected programming, and about how radio mergers should be analyzed from an antitrust perspective. The Department of Justice's focus has been on whether mergers could reduce commercial loads, increasing the prices paid by advertisers. I show that there is no evidence that this has happened for the set of allowed mergers observed in my data.

Related Literature. This paper is related to four types of literature. The first type consists of theoretical papers looking at the effects of mergers in models where firms can relocate their products (Norman and Pepall (2000), Gandhi et al. (2008)). In Gandhi et al.'s model firms choose prices and locations simultaneously in a linear city model. They compute examples where a merged firm differentiates its products while the products of the non-merging parties are crowded together in the center of the line. The location changes tend to reduce the anticompetitive price effects of a merger and can lead to the merger reducing the profits of the non-merging parties. Their examples are therefore consistent with many of the changes described in this paper. The second type of related literature contains empirical papers which examine how common ownership affects product positioning without looking specifically at what happens following mergers. Borenstein and Netz (1999) find evidence that a single airline tends to cluster the departure times of its flights more than competing airlines do. Corts (2001) finds that a movie distributor tends to differentiate the release dates of its movies.

The third type of related literature has looked specifically at the radio industry. Berry and Waldfogel (BW) (2001) examine how consolidation affects aggregate variety, measured by the number of available formats, by looking at what happened following the 1996 Telecommunications Act. The Act provided potentially exogenous variation in the extent of consolidation by permitting larger increases in the number of stations that a firm could own in larger markets. BW find that the number of available formats, and the number of formats per station, increased by more from 1993 to 1997 in the largest markets, consistent with common ownership increasing variety, although their working paper, BW (1999b), finds that there was no corresponding increase in radio listenership.

The current paper differs in its approach and, in one important respect, in the results. BW look at market-level measures, such as the format count and total listenership, consistent with using market size as an instrument. In contrast I use micro-data on the programming of individual stations to look directly at how the merging stations behave following mergers. An advantage of my approach is that I am able to show that their finding that there is no increase in total listenership results from the existence of two offsetting effects: the merging parties gain listeners while competitors lose a roughly equal number of listeners. I address the possible problem created by the lack of an instrument for station-level changes in ownership by looking closely at the timing of changes in positioning and the consistency of the results across different types of ownership changes.

The important difference in the results is that I find that the merging parties become more like competitors, explaining the redistribution of listeners, so that mergers increase measures of aggregate music variety based on playlist data only very slightly or not at all. In contrast, BW conclude that mergers increase aggregate variety. This difference has potentially important implications for welfare. As no playlist data is available for BW's time period it is impossible to know for sure why the results are different. However, I believe that there are sufficient problems with format count measures of aggregate variety that the reader should prefer my results which are based on more detailed programming information. The key problem is that format classifications evolve over time and the *Duncan's American Radio* (Duncan) classification used by BW changed between 1993 and 1997 in a way which may have affected markets of different sizes in different ways. As can be seen from BW (1999b)'s Table 1, the Duncan classification added formats such as Album Oriented Rock-New Rock, Album Oriented Rock-Progressive and Classic Hits between 1993 and 1997. The proliferation of formats appears to be more marked for Adult Contemporary and Rock programming, which are popular in larger markets, where BW find that format counts increase, than for Country and Religious programming which are more popular in rural and smaller markets. This proliferation of format labels cannot be attributed to changes in programming in large markets after the 1996 Act because Duncan begins to add formats such as AOR-New Rock and AOR-Progressive in 1994 (the "Definitions, Clarifications and Explanations" section of the Duncan books provide the classification).[2] Consistent with the particular classification system used making a material difference to the results, researchers using other classifications (which may also suffer from definitions changing over time) have come to different conclusions: for example, the Federal Communications Commission (2001), using the format classification in BIAfn's MediaAccessPro database, reports that "the number of formats has declined slightly in some of the larger markets [since the 1996 Act] while increasing in most of the smaller ones" (p. 7), which is the opposite of BW's finding.[3]

The fourth type of related literature has applied a firm-level approach to look at the effects of horizontal mergers in other industries. The emphasis in this literature has been on testing whether mergers increase prices (Borenstein (1990), Kim and Singal (1993), Prager and Hannan (1998), Sapienza (2002), Ashenfelter and Hosken (2008)) and, more recently, on whether merger simulation techniques can predict the magnitude of price changes (Nevo (2000), Peters (2006)). In contrast I focus on changes in horizontal positioning and how this affects quantities (audience size). A common finding in this literature is that any short-run price increases following mergers do not necessarily persist in the long-run (Whinston (2006), p. 115-127). Cost efficiencies after the merger provide one expla-

[2] The Duncan data is available on microfiche in many university libraries as part of the Statistical Reference Index (SRI) collection. Unfortunately it is not available electronically and publication ceased in 2002 in the face of competition from electronic databases.

[3] Previous analyses using playlist data have been much more limited. For example, Williams et al. (2002) use data for two weeks for 174 stations. The small sample forces them to look at whether stations which are likely to appeal to different listeners, such as Rock and Country stations, become more similar. In contrast, I can look at the effects of mergers for stations which are in the same broad music category.

nation for this finding, but they are also consistent with the type of repositioning patterns described here.

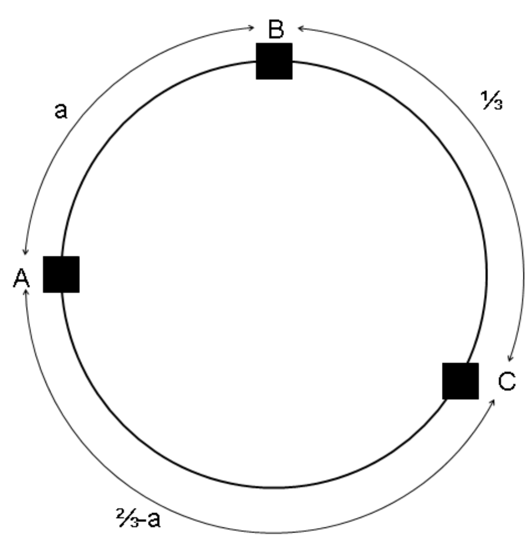
The rest of the paper is structured as follows. Section 2 summarizes the different ways in which mergers may affect programming. Section 3 describes the data. Section 4 analyzes how changes in common ownership affect differentiation and measures of variety. Section 5 examines their effects on audiences and shows that the observed changes in listenership cannot be explained by changes in commercial loads. Section 6 concludes.

2 The Theoretical Effects of Mergers on Programming

This section describes how mergers may affect programming building on the insights of Steiner (1952), Beebe (1977), Spence and Owen (1977), Gabszewicz et al. (2001), Dukes and Gal-Or (2003), Cunningham and Alexander (2004) and Anderson and Coate (2005) The footnotes provide some anecdotal evidence that these effects are recognized in the industry.

Consider a simple circular city model with three stations. For simplicity, assume that stations B and C are located on the unit circle as shown in Figure 1. In the first stage of the game A chooses

Figure 1: Location of Stations on a Circle



its location by choosing the distance a and in the second stage the stations simultaneously choose their commercial loads. Listeners are distributed around the circle, listen to at most one station and dislike commercials and travelling. When the vector of commercial loads is $\underline{c}$ the listenership of station i is given by the function $L_i(a, \underline{c})$. The price per minute per listener of a commercial is $p(\underline{c})$, so that station i's revenue is $c_i p(\underline{c}) L_i(a, \underline{c})$. The cost of choosing any location is normalized to zero so that station owners maximize revenues.[4] I now describe informally how station incentives change when A and B are commonly owned rather than separately owned. C is assumed to be owned by an independent firm. Appendix A shows how a station's first order conditions change with common ownership.

In the second stage of the game stations choose commercial loads given A's first stage location choice. Common ownership has two effects. First, a common owner will tend to increase its stations' commercial loads if they are substitutes for listeners $\left(\frac{\partial L_j(a,\underline{c})}{\partial c_i} > 0\right)$, a standard multi-product pricing effect described by Anderson and Coate (2005).[5] A reduction in the marginal costs of selling commercial time would have a similar effect and increased loads will tend to decrease station listenership. Competitors may also increase their commercial loads if loads are strategic complements. If $\frac{\partial p(\underline{c})}{\partial c_i} < 0$ then a common owner will have an offsetting incentive to reduce its stations' commercial loads to increase advertising prices. On the other hand, if advertising prices are set in a wider media market then common ownership should increase commercial loads, increasing the welfare of advertisers.

Common ownership has two types of effect on A's first stage choice of a. The first type is a direct or cannibalization effect. For given commercial loads, A takes listeners from C and loses other listeners to B as a increases. If A and B are commonly owned then A has no incentive to cannibalize

[4] Music stations purchase blanket licences from each of the major performing rights organizations ASCAP, BMI and SESAC which, for a fee proportional to the station's estimated advertising revenues, give the station the right to play any song in the organization's repetoire. Music stations do not pay per song or per play fees. For further discussion see Connolly and Krueger (2006).

[5] Dukes and Gal-Or (2003) also predict that commonly owned stations play more commercials. SchardtMedia's "Listener Choice Radio Study 2000" found that "Part of the reason the amount of commercial inventory has increased is the pressure to enhance the stock price of publicly traded companies by increasing advertising revenue. Another reason is that with station clusters, competition between stations within a market has decreased and owners have less fear that high commercial loads will chase listeners to another station. Now, they probably own the other station." (http://www.listenerchoice.com/research/RS2000.html).

B's audience so that A will tend to differentiate itself from its sister station and move towards C.[6] The second type are strategic effects arising from how a affects second stage equilibrium choices. A station has an incentive to strategically differentiate itself from competitors to soften second stage competition (increasing competitors' commercial loads). If A and B are commonly owned then A has no incentive to strategically differentiate itself from B but it still has an incentive to strategically differentiate itself from C, and this will tend to lead to A and B becoming less differentiated.[7] On the other hand, if $\frac{\partial p(\underline{c})}{\partial c_i} < 0$ then, under common ownership, A may have an offsetting strategic incentive to move towards C to toughen second stage competition, reducing C's commercial load and increasing the advertising price.[8]

While the theoretical effects on differentiation are ambiguous, it is plausible that in radio the direct effects of common ownership will be more important than the strategic effects, leading commonly owned stations to differentiate their playlists and to increase their listenership.[9] Of course, in a more general product space A would also have the option of moving away from C when it differentiates itself from B, a change that might reflect an increase in aggregate variety. However, if strategic incentives are weak then increasing variety will only be more profitable than moving towards C if it adds more listeners. If both total and category listenership are quite inelastic, consistent with the empirical results of Borenstein (1986), Rogers and Woodbury (1996) and Berry and Waldfogel (1999a), then it is plausible that commonly owned stations will find it more profitable to move towards competitors

[6] Clear Channel's Director of Urban Programming in Memphis quoted in Billboard on February 22 2003, "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?" An Infinity Programming Director in Cleveland quoted in Billboard on October 14 2000, "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."

[7] If listeners are evenly distributed around the circle, the price of commercials is fixed and transportation costs are quadratic then this effect dominates the direct effect and A and B move closer together, increase their commercial loads and lose listeners.

[8] Dukes and Gal-Or (2003) present a model with endogenous commercial loads in which separately owned stations choose minimal differentiation because a smaller quantity of commercials allows them to extract additional rents from advertisers in a bargaining game.

[9] To be precise, A will move towards C when it becomes commonly owned if, at the location chosen under separate ownership, a small increase in a results in a capture of listeners from C that is more profitable than the loss of listeners that occurs because C reduces its commercial load. This reasoning is consistent with Corts's (2001) finding that movie distributors differentiate the release dates of their own movies because price competition between movies is limited. One reason why competition in commercial loads may be limited in radio is that listeners are always able avoid commercials they particularly dislike by temporarily switching stations regardless of how many commercials the station plays.

Table 1: Extract from the Daily Log of a Classic Hits (Rock) station

Time	**Artist**	**Title**	**Release Year**
5:00PM	CLAPTON, ERIC	Cocaine	1980
5:04PM	BEATLES	While My Guitar Gently Weeps	1968
5:08PM	GRAND FUNK	Some Kind of Wonderful	1974
5:12PM	TAYLOR, JAMES	Carolina in My Mind	1976
5:16PM	RARE EARTH	Get Ready	1970
5:18PM	EAGLES	Best of My Love	1974
Stop Set	*BREAK*	*Commercials and/or Recorded Promotions*	-
5:30PM	BACHMAN-TURNER	Let It Ride	1974
5:34PM	FLEETWOOD MAC	You Make Loving Fun	1977
5:38PM	KINKS	You Really Got Me	1965
5:40PM	EDWARDS, JONATHAN	Sunshine	1971
5:42PM	ROLLING STONES	Start Me Up	1981
5:46PM	ORLEANS	Dance with Me	1975
Stop Set	*BREAK*	*Commercials and/or Recorded Promotions*	-
5:56PM	JOEL, BILLY	Movin' Out (Anthony's Song)	1977

in order to take their listeners.

3 Airplay Data

I construct measures of differentiation and variety using airplay logs provided by Mediabase 24/7, a company which collects music airplay data using electronic monitoring equipment. An extract from a log is shown in Table 1, and it lists each artist-song title combination which the station plays. Unfortunately there is no information on non-commercial talk programming. The sample consists of logs from the first week of each month from April 1998 to December 2001 for 1,094 stations, although the sample is unbalanced in several dimensions, as it expands over time and there are also a large number of missing days for individual stations.[10] When examining differentiation I aggregate the playlist data to the weekly level. There are 35,750 station-weeks of data and during a five-day week a station plays, on average, 1,367 songs (standard deviation 195) by 177 different artists (67). Oldies stations play the largest average number of artists per week (279) and Country stations play the least

[10] The number of stations in the sample expands from 702 stations in 1998 to 886 in 1999, 953 in 2000 and 1,094 in 2001. 14 weeks have less than five days of data for all stations: in particular, one week in 1998 and ten weeks in 1999 have only one day of data for all stations, while three weeks have four days of data. Overall there are 133,994 station-days of airplay logs and 766 stations are in the dataset in at least 30 different weeks.

(121).

I allocate stations to geographic markets and broad programming categories using BIAfn's Media Access Pro database (hereafter BIAfn). BIAfn also provides information on historical station ownership and quarterly station ratings. Geographic markets are defined by Arbitron, the company which estimates station audiences, and they correspond to Metropolitan Statistical Areas "subject to exceptions dictated by historical industry usage" (Arbitron (2002), p. 82). Although stations can have listeners in more than one market, I allocate each station to its BIAfn/Arbitron-identified home market which is where it gets most of its listeners and most of its local advertising revenues.[11] BIAfn groups stations in similar formats (several hundred in its classification) into broad format categories which, for simplicity, I will call categories.[12] I will use these categories to identify stations which are likely to be competing directly for listeners. The airplay sample stations are from 147 different local markets, ranging in size from New York City to Muskegon, MI, and seven contemporary music categories (Adult Contemporary (AC), Album Oriented Rock/Classic Rock (AOR), Contemporary Hit Radio/Top 40 (CHR), Country, Oldies, Rock and Urban).[13] The ownership history lists attempted transactions for each station, together with an indicator for whether the transaction was completed. BIAfn lists the closure date for the most recent transaction for each station if it is available and in other cases it provides the deal announcement date.

The airplay sample does not include every station in each category in these markets, but it does include the stations which account for the vast majority of category listenership. Table 2 provides some statistics on the coverage of the sample based on categories and listenership in Fall 2001. For example, there is an AC station in the sample from 66 of the largest 70 Arbitron markets (there are no stations from Puerto Rico which is the 13^{th} largest market). There are 221 home market AC stations in these 66 markets which have enough listeners to be rated by Arbitron, of which 162 are in

[11] Based on Arbitron data for Fall 2001, an average of 79% (70%) of the audience of a station rated in at least two (five) local markets comes from its home market.

[12] I use BIAfn's Fall 2001 classification of formats into categories, as listed in BIA Financial Network (2001), Appendix F.

[13] The music categories without stations in the airplay sample are Classical, Easy Listening, Jazz and Nostalgia/Big Band.

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

Category	Number of Market Categories (MCs) with Home to Market Stations in the Airplay Sample	Number of Home to Market Rated Stations in MCs with at least one Airplay Station	Number of Home to Market Stations in Airplay Sample	Average % of Listening to Home to Market Stations Accounted for by the Airplay Stations
Arbitron Local 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 Local 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

the airplay sample. The airplay sample stations account for, on average, 89.2% of home market AC category listening. The sample is more complete in larger markets and there are relatively few Oldies stations. On average, 13 million people were listening to the sample stations at any point during Arbitron's broadcast week (Monday-Sunday 6 am-12 pm) in Fall 2001.

This paper describes what happens when stations in the same market, and more narrowly the same market-category, change whether they are commonly owned. 1,080 stations come from 133 markets with more than one sample station observed at some point in the data. 740 stations are in the same market-category as another sample station at some point. Much of the analysis will use station-pairs and these 740 stations give 688 distinct pairs in the same market-category. 154 of these pairs are commonly owned at some point and 40 pairs change whether they are commonly owned while they are in the sample. 6 pairs are affected by two changes, so there are a total of 46 changes in common ownership for same market-category pairs. 31 changes involve switches from separate to common ownership, with 15 changes in the opposite direction. For much of the analysis I will be pooling the two types of ownership change so that I will be looking at the effects of common ownership using a set of both mergers and demergers. These changes in ownership result from different types of transaction: 19 result from trades involving a single station, 24 result from trades within a single market-category and 8 result from trades involving seven or more market-categories. 14 occur as part of divestitures required by the Department of Justice after mergers were proposed.[14] The largest geographic market experiencing a change is Los Angeles and the smallest is Colorado Springs, CO (the 96^{th} largest radio market in the country). The category experiencing the most changes is Adult Contemporary (13 changes), while there are no commonly owned pairs in the Oldies category. Of the 4,331 pairs in the same-market and different categories, 862 are commonly owned at some point with 231 changes in common ownership.

Most of the analysis will control for the number of stations in a market-category, but a few

[14] The group purchases requiring divestitures are Clear Channel's purchase of Jacor (deal closed in May 1999), Entercom's purchase of Sinclair (July 2000) and Clear Channel's purchase of AMFM (August 2000). The divestitures are listed in United States Department of Justice (1999a, 2000a, 2000b).

comments are in order about entry, exit and category switching. Exit (station closure) is very rare unless the FCC cancels a station's license for rule-breaking. In particular, there are no examples of which I am aware of a multiple station owner closing down a station, even though they might want to do so to avoid the duplication of fixed costs.[15] Entry is more common but it is severely limited by licensing and spectrum constraints. For example, the Department of Justice has argued that spectrum constraints would prevent entry from undermining market power following mergers in markets as small as Colorado Springs (United States Department of Justice (1999b)) which is the smallest market where I observe a within market-category ownership change. Eight of the airplay stations enter after January 1998. Category switching is more common, and I observe 118 category changes for the airplay stations. However, I will argue below that the most important positioning effects of mergers, at least among the stations owned by the merging parties, take place within market-categories.

4 Station Ownership and Playlist Differentiation

Section 4.1 explains how I use the playlists to measure differentiation. Section 4.2 examines how changes in ownership affect differentiation between the merging stations, and Section 4.3 looks at whether the merging stations become more similar to competitors.

4.1 Measuring Playlist Differentiation

I define a station's weekly playlist by a vector which lists how many times the station plays each artist during the week. There are 10,542 different artists listed in the logs, so the vector is (10,542x1). I use weekly playlists because music stations only update their playlists every week or so and in my data I have one week per month. When a station has one or more days of airplay logs missing, its

[15] BW (2001) find quite significant increases in the number of stations listed by *Duncan's American Radio* between 1993 and 1997. However, Duncan only lists stations with enough listeners to meet Arbitron's Minimum Reporting Standard, and the size of this set partly depends on how many diaries Arbitron sends out. Arbitron increased its sample sizes in the mid-1990s, by up to 70% in some markets ("Definitions" section of Duncan (1996)), and this is likely to have affected the number of stations listed.

weekly playlist is defined using the remaining days although dropping these weeks, or using only one day of data from each week, does not affect the qualitative results.

I present results using two different measures of differentiation although I have tried several alternatives which give similar results.[16]

Measure 1. Artists as Orthogonal Dimensions of Product Space. Stations are located in a music product space where each artist defines an orthogonal dimension of the space and a station's location is defined by each artist's share of its playlist. For example, if there were only three artists (X, Y and Z) and station i played X, Y and Z 10, 0 and 5 times respectively then i's (X,Y,Z) location would be $(\frac{2}{3}, 0, \frac{1}{3})$. The degree of differentiation (distance) between two stations is measured by the angle (in radians) between their location vectors. This distance can vary between 0 (identical playlists) to $\frac{\pi}{2}$ (no artists in common).[17] Continuing the example, if station j played X 5 times, Y 0 times and Z 10 times then the distance between i and j would be 0.6435.

Measure 2. Proportion of Unique Artists. This distance measure is based on how much a station plays artists who are not played at all by a different station during the same week. For a pair of stations i and j in week w the distance is defined as

$$\frac{\sum_{\forall a} p_{iaw}\mathrm{I}(p_{jaw} = 0) + p_{jaw}\mathrm{I}(p_{iaw} = 0)}{2}$$

where p_{iaw} is the proportion of station i's songs which are by artist a and I(.) is an indicator function. This distance varies between 0 (exactly the same artists are played by both stations) and 1 (no artists in common). In the example the distance between i and j would be zero by this measure because the stations play the same artists, even though they do so in different proportions.

[16] It is important to try several alternatives because there is no obviously correct way to measure product differentiation without information on listener tastes. The alternatives I have tried include Euclidean distance measures based on projections of artists into low dimensional spaces, correlation coeffcients and various nonlinear transformations of the measures presented here. Results are also similar using measures based on artist-song title combinations rather than artists.

[17] 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. Jaffe (1986) uses a similar angular measure to calculate the distance between firms' research activities.

The first measure uses playlists to locate stations in product space and then measures the distance between stations. This corresponds to how we would normally think about measuring differentiation. The second measure calculates the difference between playlists without defining where stations are located but it has the advantage of a more direct interpretation. For example, a 0.1 increase in the measure reflects a 10 point increase in the average percentage of songs by artists who are not played at all on the other station.

Summary Statistics. Table 3(a) contains summary statistics on the distance measures for different groups of station-pairs (in the same week) which are in the same category.[18] The upper section compares station-pairs in different markets (but the same geographic region based on the 9 Census regions) and pairs in the same market. On average, 50% of an Adult Contemporary (AC) category station's songs are by artists who are not played at all on a different, randomly-chosen AC station in a different market in the same week. For all categories except Country, there is clearly quite a lot of variation in the artists played by stations in the same category. Stations in the same market tend to be more differentiated than randomly-chosen pairs in different markets, even though any variation in tastes across markets would tend to lead to stations in the same market being more similar. This suggests that incentives for strategic differentiation exist even for pairs which are separately owned.

The lower section compares, for stations in the same market-category, distances between station-pairs which are commonly owned and those which are separately owned. There are no commonly owned Oldies stations in the same market-category. The pattern is that commonly owned stations tend to be more differentiated, although the difference for Country is small. I will show that we can see differentiation increasing after mergers, and that this increase in differentiation appears to lead to changes in listenership.

Figures 2(a) and (b) provide some evidence on the relationship between stations' nominal formats

[18] One can also compute the distance between a station's playlist in one week and its own playlist in the first week of the following month: these average distances are 0.441 and 0.085 by Measures 1 and 2 respectively. These distances increase with the length of time between weeks particularly for stations in formats where it is usual for stations to play a lot of current hits.

Table 3(a): Mean Differentiation Measures for Station-Pairs in the Same Category

	Station-Pairs in Same Category and Different Markets (Same Region)			Station-Pairs in Same Category and Same Market		
	Number of Observations	Measure 1 Artists as Dimensions of Product Space	Measure 2 Proportion of Unique Artists	Number of Observations	Measure 1 Artists as Dimensions of Product Space	Measure 2 Proportion of Unique Artists
Adult Contemporary	93,946	1.069 (0.320)	0.492 (0.250)	5,200	1.230 (0.274)	0.622 (0.225)
Album Oriented Rock/Classic Rock	31,522	0.993 (0.326)	0.424 (0.272)	1,545	1.236 (0.279)	0.628 (0.254)
Contemporary Hit Radio/Top 40	50,970	0.979 (0.281)	0.416 (0.228)	1,876	1.165 (0.286)	0.572 (0.246)
Country	53,052	0.503 (0.226)	0.110 (0.170)	1,723	0.583 (0.336)	0.173 (0.259)
Oldies	1,693	0.937 (0.453)	0.454 (0.361)	32	1.528 (0.073)	0.948 (0.073)
Rock	39,749	1.097 (0.327)	0.506 (0.281)	3,423	1.325 (0.235)	0.700 (0.222)
Urban	29,907	1.035 (0.284)	0.430 (0.232)	1,993	1.203 (0.269)	0.575 (0.236)

	Station-Pairs in Same Category & Same Market with Different Owners			Station-Pairs in Same Category & Same Market with Same Owner		
	Number of Observations	Measure 1 Artists as Dimensions of Product Space	Measure 2 Proportion of Unique Artists	Number of Observations	Measure 1 Artists as Dimensions of Product Space	Measure 2 Proportion of Unique Artists
Adult Contemporary	4,081	1.192 (0.288)	0.591 (0.231)	1,119	1.366 (0.154)	0.736 (0.153)
Album Oriented Rock/Classic Rock	1,070	1.180 (0.300)	0.576 (0.268)	475	1.364 (0.162)	0.745 (0.171)
Contemporary Hit Radio/Top 40	1,689	1.147 (0.285)	0.554 (0.244)	187	1.324 (0.240)	0.734 (0.204)
Country	1,304	0.599 (0.352)	0.183 (0.277)	419	0.531 (0.275)	0.141 (0.186)
Oldies	32	1.528 (0.073)	0.948 (0.073)	-	-	-
Rock	2,674	1.300 (0.251)	0.680 (0.235)	749	1.411 (0.131)	0.772 (0.149)
Urban	1,230	1.147 (0.310)	0.528 (0.267)	763	1.294 (0.142)	0.651 (0.146)

Notes: standard deviations in parentheses. Measure 1 ranges from 0 to 1.5708. Measure 2 ranges from 0 to 1.

Table 3(b): Mean Differentiation Measures For Station-Pairs in Different Categories

Measure 1 (*Measure 2*)

	AC	AOR	CHR	Country	Oldies	Rock	Urban
Adult Contemporary	1.08 *0.50*	1.47 *0.84*	1.35 *0.73*	1.51 *0.93*	1.49 *0.87*	1.46 *0.84*	1.53 *0.92*
Album Oriented Rock/Classic Rock		0.98 *0.42*	1.53 *0.93*	1.57 *0.99*	1.46 *0.88*	1.28 *0.67*	1.57 *0.99*
Contemporary Hit Radio/Top 40			1.01 *0.45*	1.55 *0.98*	1.55 *0.96*	1.47 *0.86*	1.36 *0.74*
Country				0.51 *0.11*	1.52 *0.95*	1.57 *1.00*	1.57 *1.00*
Oldies					0.88 *0.41*	1.53 *0.96*	1.53 *0.93*
Rock						1.14 *0.54*	1.56 *0.99*
Urban							1.07 *0.45*

Notes: Measure 1 ranges from 0 to 1.5708. Measure 2 ranges from 0 to 1. Averages calculated using all pairs of stations in the same region.

Figure 2(a): 30 Most Played Artists on Stations in the Adult Contemporary Category in the First Week of November 2001
Projected into a 2 Dimensional Music Product Space

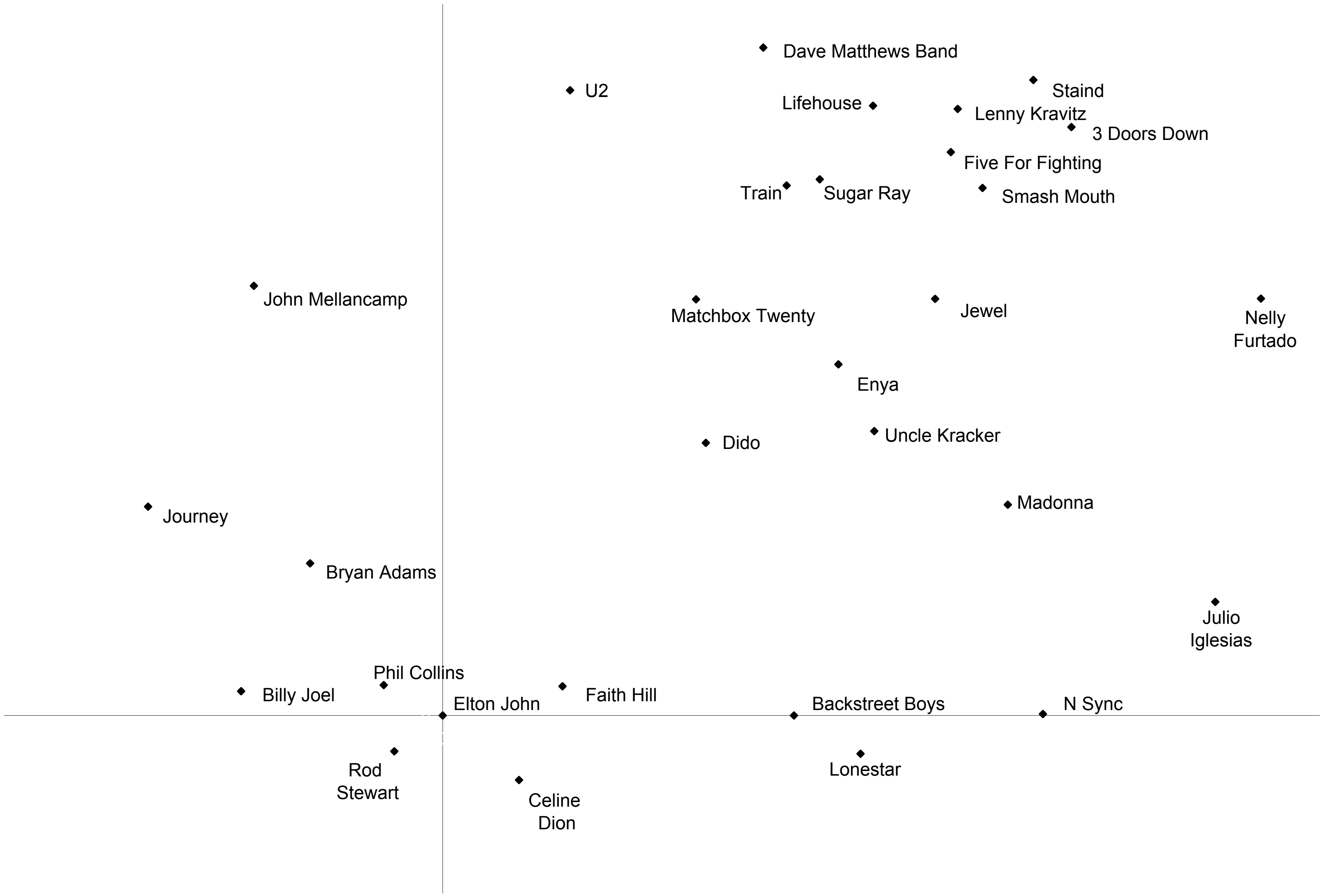
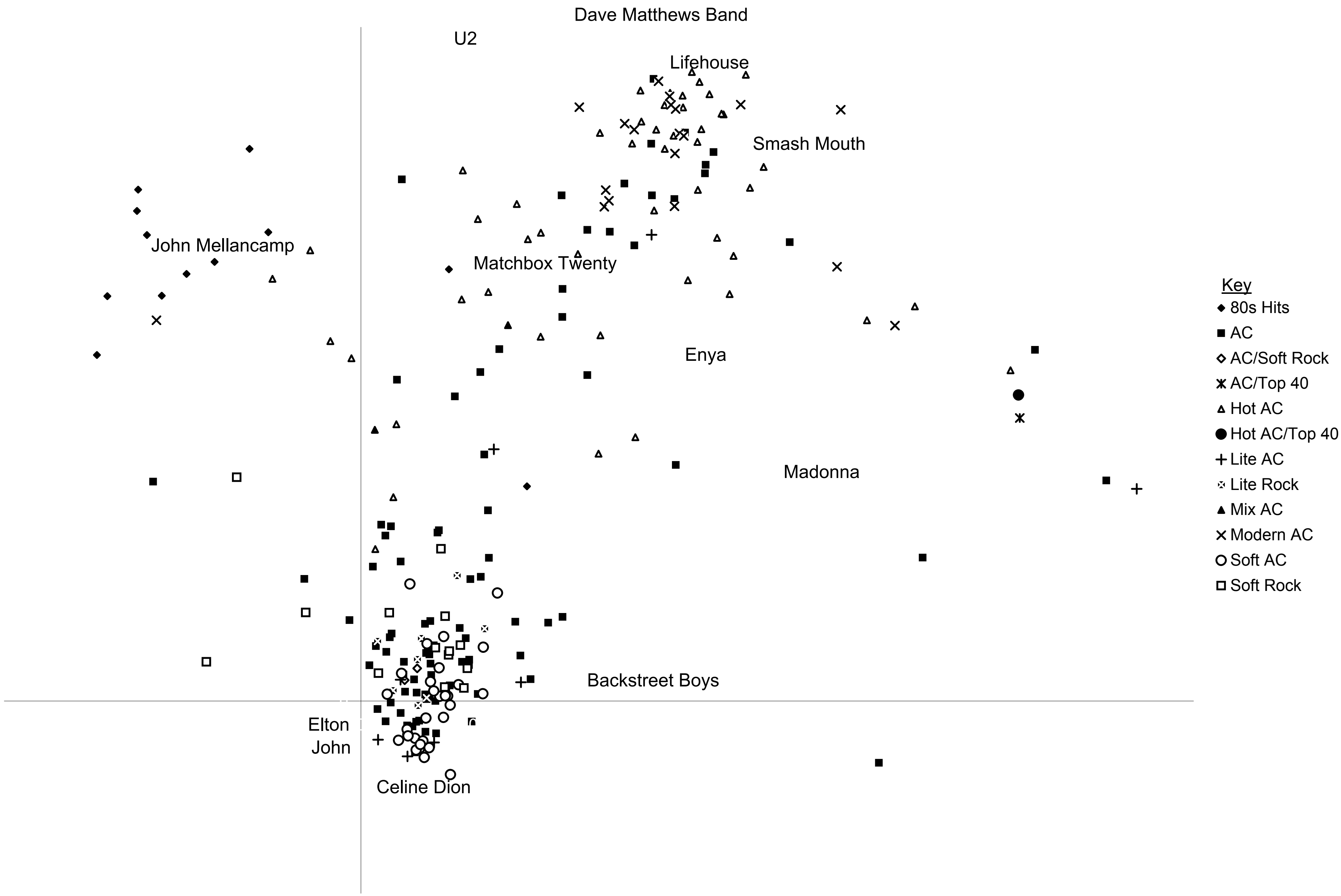


Figure 2(b): Stations in the Adult Contemporary Category in 2 Dimensional Music Product Space Based on their Playlists in the First Week of November 2001



(many within each category, apart from Country) and differentiation. They were constructed using the playlists of Adult Contemporary category stations in November 2001. The procedure is described in detail in Appendix B and it was motivated by noticing that artists who seem particularly similar tend to be played heavily by the same stations. For example, Elton John, Phil Collins, the Dave Matthews Band and U2 are all heavily played by AC stations, but stations which play a lot of Elton John also tend to play a lot of Phil Collins (correlation in their plays is 0.82) and relatively little of U2 (correlation -0.66). Instead, stations which play U2 tend to play the Dave Matthews Band (this correlation 0.72). The first stage of the procedure uses these correlations to project artists into a two dimensional space. The result for the thirty most played artists is shown in Figure 2(a). Artists are located relative to each other so that the axes have no direct interpretation and Elton John, the most played artist, is arbitrarily chosen to be at the origin. The location of the artists is intuitive with Elton John close to Phil Collins, Rod Stewart and Billy Joel while U2 and the Dave Matthews Band are in a different area of the product space. Figure 2(b) locates stations in the AC category based on the artists which they play. Stations listed in different BIAfn formats within its AC category are shown with different symbols. The locations are generally sensible with Soft Rock stations close to Elton John and Modern AC stations located closer to the Dave Matthews Band and U2. However, the diagram also illustrates two weaknesses of using formats. First, some distinct formats, such as Lite Rock, Soft Rock, Lite AC and Soft AC, are very similar.[19] Second, some stations in nominally the same format can have quite different playlists. This is particularly true in the "AC" format which has the largest number of stations. The use of playlists avoids these problems.

Most of my analysis will look at stations in the same category. Table 3(b) shows the average distances between station-pairs in different categories (both in the same and different markets). On average, there is relatively little overlap between the playlists of stations in different categories (no overlap leads to values of 1.57 and 1 for Measures 1 and 2 respectively) so that there may not be

[19] The similarity between these formats also holds using the distance measures defined above. For example, the average Measure 2 distance between two Soft Rock stations is 0.317, while the average distance between a Soft Rock station and a Soft AC station is 0.284.

much scope for a common owner to increase the degree of differentiation. The pair of categories with the most overlap is Album Oriented Rock/Classic Rock and Rock. While for consistency I will treat these categories separately in most of the analysis, I will also show that mergers cause AOR and Rock stations to become more differentiated.

4.2 Differentiation Between Stations Owned by the Merging Parties

I begin by examining what happens to the stations directly affected by the change in ownership. The regression specification is

$$d_{ijw}^{PAIR} = X_{ijw}\beta_1 + C_{ijw}\beta_2 + N_{ijw}\beta_3 + W_w\beta_4 + \varepsilon_{ijw}$$

where d_{ijw} is the distance between stations i and j in week w and C and W are category and week dummies. X is a dummy variable equal to 1 if i and j are commonly owned. Standard errors are calculated following the panel data procedure of Driscoll and Kraay (1998), which allows for heteroskedasticity, correlations across panels (station-pairs), and I specify that may be up to 4 months of time-series correlation. I report Driscoll-Kraay standard errors throughout the paper except in cases where the model is non-linear, in which case standard errors are calculated using a resampling bootstrap (see notes beneath the relevant table). The baseline specifications use station-pairs which are in the same local market and the same music category.

The optimal degree of differentiation may depend on how many other stations are in the category, and this can vary over time because of category switching. N contains two sets of dummies for the number of stations in the market-category. The first set is based on the count of all stations in the category, while the second set are based on the count using only stations which are ever in the airplay sample (these stations tend to be larger). I include these two sets of dummies whenever I control for the number of stations in this paper.

Pairs in the Same Category. The specification in column (1) of Table 4 does not include

Table 4: Differentiation Between Stations Owned by the Merging Parties

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	No Pair Fixed Effects	Pair Fixed Effects	Pair Fixed Effects	Pair Fixed Effects Different Effects for Pairs Going to and From Common Ownership	Pair Fixed Effects Different Effects for Pairs in Different Markets	Pair Fixed Effects Different Categories	Pair Fixed Effects Different Categories with Different Effects for Similar Stations
Sample	All Same Market & Category	All Same Market & Category	Market-Categories with ≥3 Observed Stations	All Same Market & Category	All Same Category (includes different markets)	Same Market & Different Categories	Same Market & Different Categories
Measure 1: Artists as Dimension of Product Space							
Same Owner	0.1384***	0.0837***	0.1208***	-	0.0888***	0.0094***	0.0037**
	(0.0079)	(0.0097)	(0.0188)		(0.0096)	(0.0026)	(0.0018)
Same Owner*Different Geographic Market	-	-	-	-	-0.0998***	-	-
					(0.0107)		
Same Owner*"Ever Similar Programming"	-	-	-	-	-	-	0.0361***
							(0.0088)
Same Market-Category & Same Owner	-	-	-	0.0762***	-	-	-
* Become Commonly Owned				(0.0138)			
Same Market-Category & Same Owner	-	-	-	0.1250***	-	-	-
* Become Separately Owned				(0.0218)			
Measure 2: Proportion of Unique Artists Played							
Same Owner	0.1208***	0.0689***	0.0901***	-	0.0719***	0.0098***	0.0031**
	(0.0070)	(0.0085)	(0.0150)		(0.0086)	(0.0028)	(0.0008)
Same Owner*Different Geographic Market	-	-	-	-	-0.0772***	-	0.0258***
					(0.0094)		(0.0084)
Same Owner*"Ever Similar Programming"	-	-	-	-	-	-	-
Same Market-Category & Same Owner	-	-	-	0.0757***	-	-	-
* Become Commonly Owned				(0.0141)			
Same Market-Category & Same Owner	-	-	-	0.0806***	-	-	-
* Become Separately Owned				(0.0077)			
Station-Category-Pair Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
<u>Control Dummies</u>							
Category Dummies	Yes	No	No	No	No	No	No
Number of Station Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared (Measure 1)	0.4200	0.0428	0.0451	0.0457	0.0686	0.0125	0.0125
Number of Observations	15,792	15,792	15,792	15,621	316,631	118,819	118,819

<u>Notes:</u> Standard errors in parentheses calculated following Driscoll-Kraay (1998), allowing for correlation across panels (station-pairs) and 4 months of time-series correlation. ***,**,* denote statistical significance at the 1, 5 and 10% levels. Number of station dummies include dummies for the total number of stations in the format and the number of stations in the format which are ever in the airplay sample. Measure 1 and 2 results come from separate regressions.

pair fixed effects. Consistent with the summary statistics presented above the same owner coefficients indicate that commonly owned stations tend to be more differentiated than those which are separately owned. On average, 55% of a station's songs are by artists not played at all by a separately owned station in the same market-category, and the Measure 2 coefficient implies a 12 percentage point or 21% increase for stations with the same owner. The specification in column (2) includes station-category-pair fixed effects, so that the ownership coefficients are only identified from what happens following ownership changes. Common ownership is associated with significant increases in differentiation although the coefficients are 40% smaller than in column (1).

Below I will show that commonly owned stations become more like competitors using observations from market-categories where I observe at least 3 stations. The column (3) specification repeats column (2) using this subset of markets and there are 26 changes in common ownership for pairs in this group. The ownership coefficients are slightly larger than in column (2). The coefficients are also statistically significant (0.0603 (0.0134) for Measure 1 and 0.0597 (0.0124) for Measure 2) using only market-categories with two airplay stations.

Column (4) allows for different effects for pairs which become and cease to be commonly owned. The 6 pairs which experience both types of changes are excluded. Both types of ownership change have significant effects, i.e., stations which cease to be commonly owned become less differentiated, and, especially by Measure 2, the magnitude of the changes are also similar.

The first six lines of Table 5 repeat the specifications in columns (1) and (2) for each category separately, excluding Oldies in which no market-category pairs are commonly owned. Even though the number of changes in common ownership is small in each category, the differentiation effects are significant for all categories except Country. The Country coefficients, and the fact that all Country stations have similar playlists (Table 3(a)) suggest that Country listeners may have homogenous tastes so that a common owner differentiating Country stations would only tend to lose listeners.

The theoretical explanation for why a common owner should increase the degree of differentiation between its stations is that it wants to prevent them cannibalizing each other's audience. As stations

Table 5: Differentiation Between Stations Owned by the Merging Parties - By Category

	Average Pair Distance		Number of Pairs in Same Market		**Measure 1**		**Measure 2**	
					(1)	(2)	(3)	(4)
					No Pair FEs	Pair FEs	No Pair FEs	Pair FEs
Category	Measure 1	Measure 2	Ever Commonly Owned	Change Common Ownership	Same Owner	Same Owner	Same Owner	Same Owner
Adult Contemporary	1.2295	0.6220	46	13	0.1782***	0.1305***	0.1503***	0.1139 ***
					(0.0086)	(0.0161)	(0.0053)	(0.0184)
Album Oriented Rock	1.236	0.6279	17	5	0.2128***	0.1195***	0.1968***	0.0763***
					(0.0143)	(0.0354)	(0.0116)	(0.0294)
Contemporary Hit Radio	1.1645	0.5722	11	4	0.2052***	0.1580***	0.2096***	0.1998***
					(0.0459)	(0.0325)	(0.0387)	(0.0468)
Country	0.5828	0.1729	16	6	0.0095	0.0197	0.0124	0.0094
					(0.0360)	(0.0130)	(0.0258)	(0.0065)
Rock	1.3245	0.7004	32	12	0.1010***	0.0453***	0.0827***	0.0339**
					(0.0049)	(0.0140)	(0.0058)	(0.0140)
Urban	1.2035	0.5753	32	6	0.1440***	0.1301***	0.1231***	0.0977**
					(0.0145)	(0.0428)	(0.0105)	(0.0449)
One Rock, One AOR	1.3589	0.7422	60	14	0.1306***	0.0429***	0.1302***	0.0426***
					(0.0069)	(0.0095)	(0.0071)	(0.0119)

Notes: see Table 4. Regressions correspond to those in columns (1) and (2) in that table.

in different geographic markets do not compete for the same listeners, there is no reason for a common owner to differentiate these stations. The specification in column (5) of Table 4 includes all pairs which are in the same category and region and allows for common ownership to have different effects for pairs in the same market and those in different markets. The coefficients show that, consistent with the theory, only pairs in the same market become more differentiated. Across markets there is a small, but significant, homogenization effect which is consistent with the existence of some economies of scope from playing the same music on different stations.[20]

Pairs in Different Categories. Common ownership may also affect the positioning of stations across categories, either because some listeners substitute between stations in different categories or because the ownership change affects which category the owner wants the station to be in.

The station-pair fixed effects specification in Column (6) of Table 4 uses pairs in the same market and different categories. The ownership coefficients are both positive, indicating that common ownership tends to lead to differentiation, but they are much smaller than for stations in the same category, even though the average distance between stations is larger (the average value of the dependent variable for separately owned pairs is 1.50 for Measure 1 and 0.90 for Measure 2). There are stronger differentiation effects for pairs in different categories which are more similar. Column (7) of Table 4 allows for a different effect for pairs which have similar playlists at some point. I define the "Ever Similar Programming" dummy as being equal to 1 if the Measure 1 distance is ever less than 1.2 or the Measure 2 distance is ever less than 0.7, although the results are similar when these arbitrary cutoffs are varied.[21] The last line of Table 5 examines pairs where one station is in the Album Oriented Rock/Classic Rock category and the other station is in the Rock category. Table 3(b) shows that these categories are quite similar, and there is a relatively large number of pairs in these categories which change whether they are commonly owned. The differentiation effects are

[20] The most plausible type of economy of scope is that stations may share music research which helps guide programming directors about which songs to choose. Sweeting (2006) investigates this issue more closely.

[21] One can also perform a similar analysis for pairs in the same category as not all of them meet the close criterion. This shows that the increases in differentiation come for the 35 pairs which are close by these definitions. This is sensible as there are likely to be small gains from differentiating stations which are already playing quite different music.

similar to those for pairs where both stations are in the Rock category.

Category Switching. I focus on the effects of common ownership on differentiation between stations which are in the same category and which remain in the same category. This treatment assumes that the effects of common ownership on category switching are much smaller. The data supports this assumption. There are 182 cases of pairs of stations in the same market which become commonly owned. After these mergers, there are only 3 cases of the common owner switching a station across a category so that it goes from not having a commonly owned sister station in a category to having a sister station. Two of these moves involve a switch between AOR/Classic Rock and Rock, which are not so clearly distinct as other categories. There is only one move in the opposite direction i.e., where a station goes from having a sister station in its category to not having a sister station.

Addressing the Endogeneity Concern. Firm or establishment-level merger studies suffer from the lack of an instrument for firm-level changes in ownership. In my context, endogeneity involves two concerns. First, the changes in differentiation may have happened even without the change in common ownership, with some common factor leading to both the change in programming and the change in ownership. Second, even if the change in ownership causes the change in differentiation, the stations which experiences changes in common ownership may not be representative. For example, owners may have more incentive to merge when their stations are fighting particularly intensely for listeners. I now show, using observations for pairs in the same market-category, that the evidence does not support these concerns as being important.

Comparison of Pairs Changing Ownership with Other Pairs. I test whether pairs which change commonly ownership are representative by examining whether they display a similar degree of differentiation when they are separately owned. I do this by estimating a regression using observations on all separately owned pairs in the same market-category, where the dependent variable is the distance measure and the explanatory variables are all of the controls used previously (without pair fixed effects, but including category dummies) and a dummy for whether the pair experiences a change in whether it is commonly owned. For both of the distance measures the coefficients on the change common ownership dummy are very small and statistically insignificant even at the 90% level (e.g., the coefficient is -0.0011 (0.0113) for Measure 1).[22] Separately owned stations which change common ownership are differentiated to the same degree as pairs which are always separately owned.

Timing of the Change in Differentiation. I use two approaches to test for evidence that the change in differentiation would have happened without the change in common ownership. Column (1) of Table 6(a) shows the coefficients on the same owner variable when the regression includes pair-specific time trends as well as pair fixed effects. The same owner effects are smaller than in column (2) of Table 4 but they remain statistically significant at the 1% level. Table 6(b) reports the coefficients from a pair fixed effects regression which looks precisely at when the change in differentiation takes place. The regression excludes pairs which ever switch from common to separate ownership, and it allows for separate differentiation effects in several quarters around the merger. The merger happens (based on the date in the BIAfn database) between Quarter -1 and Quarter 1 and the Quarter -1 coefficient is normalized to zero. The Quarter -3 dummy therefore tests whether the pair is more differentiated three quarters before the merger than it was one quarter before the merger. The pattern of the coefficients reveals no significant pre-merger trends, while the increase in differentiation happens in the three quarters following the merger but is completed within one year. These results may actually understate how quickly the change in positioning occurs because some of the BIAfn dates refer to the date when the deal was announced rather than the date when it closed. Changes in station management may also happen some time after the deal closes.

Consistency Across Different Types of Mergers. As explained in Section 3, the changes in ownership in the data are associated with different types of transaction. The endogeneity concern may be most pronounced when a single station or market-category is involved. Table 6(a) column (2) shows the ownership coefficients from the pair fixed effects regressions where I allow for different effects for two types of ownership change: those involving less than 7 market-categories (small mergers,

[22] One can also perform a similar regression to look at whether pairs which experience a change in common ownership look like pairs which are always commonly owned when they are commonly owned. In this case one finds that they look slightly less differentiated but the difference is small and statistically insignificant at the 5% level when one excludes the year following the change in ownership.

Table 6: Differentiation Between Stations Owned by the Merging Parties - Robustness Checks

6(a): Pair-Week Trends and Different Types of Transaction

	(1)	(2)
Specification	Pair Fixed Effects & Pair-Week Time Trends	Pair Fixed Effects Differential Effects For Different Types of Transaction
Sample	All Same Market & Category	All Same Market & Category
Measure 1: Artists as Dimension of Product Space		
Same Market-Category & Same Owner	0.0526***	-
	(0.0110)	
Same Market-Category & Same Owner * Large Merger		0.0823***
		(0.0127)
Same Market-Category & Same Owner * Small Merger		0.0843***
		(0.0118)
Measure 2: Proportion of Unique Artists Played		
Same Market-Category & Same Owner	0.0360***	
	(0.0088)	
Same Market-Category & Same Owner * Large Merger		0.0587***
		(0.0073)
Same Market-Category & Same Owner * Small Merger		0.0733***
		(0.0114)
Station-Category-Pair Fixed Effects	Yes	Yes
Control Dummies		
Number of Station Dummies	Yes	Yes
Week Dummies	Yes	Yes
Adj. R-Squared	0.9527	0.0428
Number of Observations	15,792	15,792

Notes: see Table 4. Adj R-squared in column (1) includes the dummies and time trends. See text for definition of small and large mergers.

6(b): Time Path of Changes in Differentiation

	(1)	(2)
Specification	Differentiation Relative to Date of Merger	
Sample	All Same Market & Category Excluding Pairs Which Cease to Be Commonly Owned	
	Measure 1	Measure 2
Quarter Relative to Merger		
-4 or more	0.0252	0.0260
	(0.0271)	(0.0306)
-3	-0.0170	-0.0244
	(0.0165)	(0.0162)
-2	-0.0193	-0.0189
	(0.0180)	(0.0219)
-1	0	0
	-	-
1	0.0268	0.0304
	(0.0242)	(0.0241)
2	0.0664***	0.0654***
	(0.0204)	(0.0243)
3	0.0905***	0.0779***
	(0.0219)	(0.0245)
4	0.1098***	0.0977***
	(0.0257)	(0.0216)
5 or more	0.0865***	0.0986***
	(0.0249)	(0.0246)
Station-Category-Pair Fixed Effects	Yes	Yes
Control Dummies		
Number of Station Dummies	Yes	Yes
Week Dummies	Yes	Yes
Adj. R-Squared	0.0439	0.1169
Number of observations	15,298	15,298

Notes: see Table 4.

38 changes in ownership) and those involving 7 or more market-categories (large mergers, 8 changes in ownership with the median number of market-categories affected equal to 54).[23] The effects of common ownership on differentiation are almost identical for the two groups.[24]

4.3 Differentiation between the Merging Stations and Competitors

I now turn to the question of whether commonly owned stations become more similar to other stations in the same category. The analysis uses 112 market-categories where I observe at least three stations. The results in column (3) of Table 4 show that common ownership leads stations in this subset of market-categories to become more differentiated.

To look at whether a common owner makes its stations more similar to stations owned by competitors I measure the distance between each station and each pair of other stations in the same market-category. The distance between a station and a pair of stations is simply the minimum of the distances between the station and each member of the pair. For example, if the station is A and the members of the pair are B and C then the distance from A to the pair is the minimum of the AB and AC pair distances (Figure 3). I want to test whether the station and the pair tend to be closer together when the pair is commonly owned by a firm which does not own the station. The regression specification is

$$d_{ijkw} = X_{ijkw}\beta_1 + C_{iw}\beta_2 + N_{iw}\beta_3 + W_w\beta_4 + \varepsilon_{ijkw} \quad (1)$$

where d_{ijkw} is the distance between i and the pair jk in week w, and X is a dummy variable which is equal to 1 if both j and k are owned by the same firm and this firm does not own i. The category, week and number of station dummies are the same as in the regressions in Table 4.

The results are presented in Table 7(a) for the two distance measures. The coefficients in columns (1) and (3) come from regressions without fixed effects. The negative coefficients indicate that a

[23] A pair is allocated to the small merger group if any transaction involved less than 7 market-categories.

[24] The coefficient on common ownership when I exclude pairs which are not affected by divestitures mandated by the Department of Justice are also similar (e.g., Measure 1 coefficient is 0.0982 (0.0273)). However, as these divestitures result from potentially endogenous mergers, and may have been negotiated between the firms and Department of Justice, the changes to these pairs should not necessarily be treated as being more likely to be exogenous than those for other pairs.

Table 7: Differentiation Between The Merging Parties and Competitors & Effects of Mergers on Market-Category Variety

7(a): Differentiation Between A Station and a Pair of Stations

	Measure 1		Measure 2	
	(1) No Station-Group Fixed Effects	(2) Station-Group Fixed Effects	(3) No Station-Group Fixed Effects	(4) Station-Group Fixed Effects
Pair are commonly owned	-0.0988 (0.0082)***	-0.0910 (0.0145)***	-0.0772 (0.0069)***	-0.0643 (0.0137)***
Station-Category-Group Fixed Effects	No	Yes	No	Yes
Control Dummies				
Category Dummies	Yes	No	Yes	No
Number of Station	Yes	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes	Yes
Adj. R-squared	0.2376	0.0610	0.2207	0.1781
Number of observations	14,475	14,475	14,475	14,475

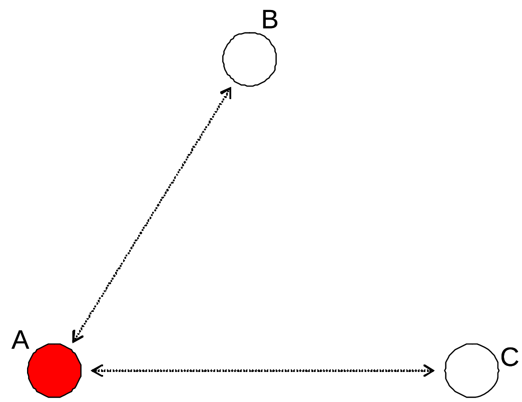
Notes: see Table 4. Observations from market-category weeks with at least three stations.

7(b): Market-Category Variety

	Average Measure 1 Distance Between Station-Pairs		Average Proportion of Unique Artists on Each Station		Concentration of Combined Market-Category Playlist	
	(1) No Market-Category Fixed Effects	(2) Market-Category-Observed Group Fixed Effects	(3) No Market-Category Fixed Effects	(4) Market-Category-Observed Group Fixed Effects	(5) No Market-Category Fixed Effects	(6) Market-Category-Observed Group Fixed Effects
Number of owners	-0.0111 (0.0045)**	-0.0122 (0.0107)	-0.0153 (0.0046)***	-0.0107 (0.0097)	-0.0024 (0.0056)	-0.0063 (0.0233)
Observed Station--Category-Group Fixed Effects	No	Yes	No	Yes	No	Yes
Control Dummies						
Category Dummies	Yes	No	Yes	No	Yes	No
Number of Station	Yes	Yes	Yes	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.6310	0.1120	0.5309	0.3795	0.6194	0.1018
Number of obs.	2,436	2,436	2,436	2,436	2,436	2,436

Notes: see Table 4. Observations from market-category weeks with at least three stations.

Figure 3: Differentiation Between a Station and a Station-Pair



station tends to face closer competition from a pair of other stations in the same market-category when that pair is commonly owned. The average Measure 2 distance between a station and a pair of stations which do not have the same owner is 0.51 i.e., 51% of the station's songs are by artists not played on the member of the pair which is most similar to it. The coefficient in column (3) implies that this percentage is 8 points (16%) lower when the pair are commonly owned by a firm that does not own the station. The specifications reported in columns (2) and (4) include station-pair combination fixed effects (e.g., a station A-pair BC dummy). The coefficients are similar to those in columns (1) and (3) and they are statistically significant at the 1% level.

This pattern is what we would expect if category listenership is inelastic with respect to what is played so that a common owner has more incentive to try to increase the audience of its stations by taking listeners from other stations rather than by trying to increase category listenership. This suggests that common ownership may not increase measures of aggregate variety constructed from the playlist data, a prediction which I now show is correct.

Aggregate Variety. I consider three different measures of variety. The first measure is simply the average of the Measure 1 pair-distances between the observed stations in a market-category. One can think of this as measuring variety by average differentiation. The second measure reflects how much each station's playlist adds to playlists of other stations in the market-category. To be precise, it is defined as

$$\frac{\sum_{i=1}^{n_{mw}} \sum_{\forall a} p_{iaw} \mathrm{I}\left(\sum_{j \neq i} p_{jaw} = 0\right)}{n_{mw}}$$

where p_{iaw} is the proportion of station i's songs which are by artist a, I(.) is an indicator function and n_{mw} is the number of observed stations in the market-category. The average value of this measure for market-categories with at least three observed stations is 0.38 (standard deviation 0.15), meaning that just over one-third of each station's playtime is devoted to artists who are not being played on other stations in the same market-category. The third measure looks at the amount of variety provided by the aggregate market-category's playlist formed by combining the playlists of the individual stations. It is defined as $-\sum_{\forall a} p_{maw}^2$ where p_{maw} is the proportion of songs in market-category m's playlist which are by artist a. The measure increases as the aggregate playlist becomes less concentrated. The average of this measure is -.009 (0.004) and I use its natural log in the regressions. The regression specification for each measure is

$$v_{mw} = X_{mw}\beta_1 + C_m\beta_2 + N_{mw}\beta_3 + W_w\beta_4 + \varepsilon_{mw} \qquad (2)$$

where v_{mw} is the variety measure in market-category m in week w. C and W are category and week dummies and N are dummies for the number of stations in the market-category.[25] X is a count of how many different firms own the observed stations. A negative coefficient on this variable implies that common ownership is associated with greater variety. An observation is a market-category-week and I only use market-category-weeks where I observe at least three stations.

Table 7(b) presents the results. The regressions in columns (1), (3) and (5) do not include market-category dummies. The coefficients on the number of owners are negative, consistent with

[25] Dummies for the number of observed stations in the market-category-week are included in the regressions in addition to the two sets of number of station dummies used in the regressions in Table 4. This is necessary because the variety measures tend to vary systematically with the number of observed stations. Including these additional dummies in the earlier regressions does not change any of the results.

common ownership increasing variety within the market-category, and they are statistically significant in columns (1) and (3) but the coefficients are quite small in size (the mean and standard deviations of the dependent variables are 1.20 (0.20) and 0.38 (0.15)). The remaining columns report the results for market-category fixed effect regressions. I define separate fixed effects for the set of stations being used in the calculation of the variety measure. With fixed effects, all of the coefficients are small and insignificant, indicating that changes in the number of owners do not lead to significant increases in variety. This result is particularly convincing because the fact that I do not observe all stations in a category is likely to bias me towards finding that consolidation does increase variety. The reason is that when I observe sample stations becoming commonly owned they may be becoming more similar to stations which are not in the airplay sample as well as those which are, so I will miss some of the declines in differentiation when I measure variety using only stations in the airplay sample.

5 Station Listenership and Common Ownership

I now examine whether the changes in positioning are associated with changes in audiences (which would correspond to quantities in other industries). I find that mergers lead to a redistribution of listeners across stations, with gains for the merging parties and losses to competitors.

I use Arbitron audience data, which is part of the BIAfn database, from the Spring and Fall quarters each year from Spring 1998 to Fall 2001.[26] Arbitron estimates audiences using diaries completed by a sample of listeners. Following industry conventions, I define a station's listenership share as the proportion of the population aged 12 and above who listen to the station during an average quarter hour in Arbitron's broadcast week (Monday-Sunday 6 am-midnight).[27] The average share for a station in the airplay sample is 0.0084 (standard deviation 0.0041), i.e., on average 0.84% of the

[26] Arbitron only surveys some markets twice a year, and my version of the BIAfn database only contains Spring and Fall data for all markets prior to 2000.

[27] BIAfn provides data on Arbitron's estimates of each station's share of r*adio listening* by people aged 12 and above in each market in each Spring and Fall quarter, known as the Average Quarter Hour (AQH) share. This was combined with data from *Duncan's American Radio* and M Street's STAR database on the Average Persons Rating (APR) for each market, which measures the average proportion of people aged 12 and above listening to radio in each quarter hour. Combining these numbers gives the average proportion of the population aged 12 and above who are listening to each station. Observations from Birmingham, AL in Fall 2001 were dropped because of missing APR data.

market's population is listening to the station at any point during the broadcast week. The highest observed share is 0.0376 for a Country station in Knoxville, TN, in Fall 1998. Radio listening declined by 9.1% between 1998 and 2001 in the airplay markets, although this trend cannot be attributed to increased ownership concentration as it dates back to the late 1980s before any ownership reforms.[28]

To match the previous analysis Table 8 reports the results from a set of regressions using the pairs of stations in the same market-category for which I have airplay data.[29] A pair is only included if both stations are in the playlist data for at least one week during the quarter. Sweeting (2004) provided an analysis of the effects of common ownership on audiences for a much wider sample of stations using a nested logit model, with results that are consistent with those presented here. As before, I report Driscoll-Kraay standard errors, which allow for correlation in the residuals across pairs, and I specify that there may be two periods (1 year) of time-series correlation.

The dependent variable in column (1) is the natural logarithm of the pair's combined listenership share. The specification includes station-pair fixed effects, a dummy for whether the pair is commonly owned, number of station and ratings quarter dummies. 34 changes in common ownership identify the same owner coefficient. This is smaller than the number of changes in the analysis of differentiation because the coarseness of the airplay data (two observations per year) and the rapid reversal of some of the ownership changes. The ownership coefficient implies that common ownership is associated with a 2.7% increase in listenership which is statistically significant at the 10% level.

The differentiation analysis indicated that common owners move their stations in the year following the merger. In column (2) I drop the observations in the year following the ownership change and the ownership effect increases to 7.7% and it is statistically significant at the 1% level. This change in the coefficient is consistent with both stations taking some time to adjust their programming and with it taking some time for listeners to adjust to programming changes.[30] If one includes pair-time

[28] Duncan (1999), Spring 1999 National Rankings Supplement, p. 2.

[29] I also investigated whether common ownership affects the listenership of stations in the same market but different categories. I found no significant effects even though I do find small but statistically significant increases in differentiation for these pairs. This difference in the results may be explained by the fact that is hard to identify small effects in the relatively coarse and noisy listenership data compared with the very detailed data on station airplay.

[30] If pairs switching from common to separate ownership are excluded and a dummy is included for the year following

Table 8: Mergers, Station Listenership and Category Exit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification	Station-Pair Fixed Effects	Station-Pair Fixed Effects	Station-Pair Fixed Effects	Station-Pair Fixed Effects	Station-Pair Fixed Effects	Station-Pair Fixed Effects	Station-Pair Fixed Effects Conditional Poisson	Station-Pair Fixed Effects Conditional Poisson
Sample (airplay pairs only)	All Same Market & Category	All Same Market & Category	All Same Market & Category	All Same Market & Category	Same Market & Category With More Than Three Obs. Stations	Same Market & Category With More Than Three Obs. Stations	All Same Market & Category	All Same Market & Category
Drop 12 months following change in common ownership	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dependent variable	Log of pair's combined share	Log of pair's combined share	Pair's combined share	Combined share of all other stations in market-category	Pair's combined share	Combined share of all other stations in market-category	Number of other stations in market-category	Number of other airplay stations in market-category
Same Owner	0.0271 (0.0143)*	0.0769 (0.0151)***	0.00098 (0.00025)***	-0.00100 (0.00022)***	0.00115 (0.00013)***	-0.00111 (0.00041)***	-0.2844 (0.1890)	-0.3701 (0.1238)***
Station-Category-Pair	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Dummies								
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Station Dummies	Yes	Yes	No	No	No	No	No	No
Adjusted R^2	0.2468	0.2559	0.2276	0.0120	0.2295	0.0419	-	-
Number of Observations	3,023	2,947	2,947	2,947	1,767	1,767	2,947	2,947

Notes: see Table 4. Driscoll-Kraay standard errors in parentheses for columns (1)-(6) allowing for correlation across panels (station-pairs) and one year (two quarters in my data) of time-series correlation. Standard errors for columns (7) and (8) calculated using a resampling boostrap with 50 repetitions clustered on the market.

trends the common ownership coefficient increases to 0.2044 (0.0576).

Columns (3)-(6) compare what happens to the combined listenership of the merging stations with what happens to the combined listenership of competitors. As I am interested in whether the same number of listeners are gained by the merging firms and lost by competitors the dependent variable is the share in levels rather than logs. The specifications also exclude dummies for the number of stations in the market-category, so that I can look at how many people listen to other stations in the category without conditioning on how many other stations are in the category. I look separately at what happens to the number of competitors in a moment. Given the results in columns (1) and (2) I drop the 12 months following the change in common ownership.

The pair's own combined share is the dependent variable in column (3). The coefficient implies that common ownership increases the pair's listenership by an average of 7.1%. This is close to the percentage effect implied by the log regression in column (2). The combined listenership of *all of the other* stations in the market-category, including stations which are not in the airplay sample, is the dependent variable in column (4).[31] The coefficient is negative and its absolute value is almost identical to the coefficient in column (3), indicating that other stations lose, on average, almost exactly the same number of listeners as a pair of stations which become commonly owned gain. An alternative specification has total category listenership as the dependent variable: in this case the common ownership coefficient is -0.00002 (0.00047) indicating that common ownership of the pair does not change category listenership. This finding is consistent with category listenership being quite inelastic.

My finding that merging stations become more like competitors was based on the subset of market-categories where I observe three stations. Columns (5) and (6) repeat columns (3) and (4) for this subset, and the coefficients are similar. In a separate regression using only the combined listenership of *other airplay* stations as the dependent variable the coefficient is -0.00056 (0.00021). Commonly

the merger then this first year effect is 0.0230 (0.0114).

[31] On average there are two other stations in a market-category with enough listeners to be rated by Arbitron. In quarters where no other stations are rated the dependent variable is equal to zero. The results are very similar using tobit models to deal with these quarters.

owned stations therefore appear to take listeners from both airplay and other stations. This suggests that commonly owned stations are becoming more like stations which are not in the sample, so that I am likely to be biased towards finding that mergers between stations in my sample increase measure of aggregate variety constructed using only the airplay stations.

A couple of back-of-the-envelope calculations illustrate the economic significance of the redistribution of listeners. Ordering the pairs changing common ownership by audience size, the median pair are two stations in Cincinnati, OH with a combined average quarter hour audience of 24,848 people aged 12 and above in Spring 2000. An increase of 7.1% would increase this audience by 1,764 listeners per quarter-hour. The results imply that a similar number of listeners would be lost from category competitors. BIAfn estimates that the combined annual revenues of these Cincinnati stations was $17.7 million in 2000. If revenues increase in proportion to the size of the audience then the common ownership effect would imply a revenue increase for the merging stations of around $1.25 million.[32]

Competitive pressure may cause some competitors to leave the category. Columns (7) and (8) examine the effects of common ownership on the number of stations in the market-category using conditional fixed-effects Poisson models. The dependent variable in column (7) is the number of other stations in the category (i.e., not counting the pair). The average number of other stations is 2.6 and it ranges from 0 to 13. The dependent variable in column (8) is the number of other airplay stations in the market-category[33], and its range is 0 to 4 with an average of 1.1.[34] The coefficients imply that common ownership of a station-pair is associated with the number of (all) other stations falling by 0.65 and the number of other airplay stations falling by 0.32, with the latter effect statistically significant. This is consistent with mergers increasing the pressure on competitors. Note that these declines reflect competitors switching to other categories rather than exiting the market: for example, no airplay stations close down during my data. The switches, which involve competitors moving

[32] The BIAfn station revenue estimates are calculated using a proprietary BIAfn formula and are not based on reports by the stations.

[33] The count is based on the number of stations which are ever observed in the airplay sample not just the number of stations which are observed in the airplay sample in a particular week.

[34] This count includes airplay stations which have not yet entered the airplay sample or have missing airplay logs in a particular ratings quarter.

away from the merging parties, are also inconsistent with the type of repositioning considered in the *Horizontal Merger Guidelines*.

Table 9 reports the results of using observations on station listenership rather than pair listenership. I use this specification to examine whether changes in station listenership when local common ownership changes may instead reflect the effects of changes in the extent of national ownership. For example, if there are economies of scope in providing quality programming on many stations then stations owned by large national firms may tend to get more listeners. The sample consists of all of the airplay sample stations while they are observed in the airplay sample. The dependent variable is the log of the station's own market share. The explanatory variables are a count of how many other airplay stations are owned by the station's owner in its local market-category (own local common ownership), an indicator variable for whether other stations in the market-category are commonly owned by different firms (other local common ownership) and the log of the number of stations which the station's owner owns in the same category nationwide (own national ownership, the mean number is 24 and the maximum is 146). All of the specifications control for the number of stations in the local market-category.

The specification in column (1) does not include station-category fixed effects. Both of the own ownership coefficients are positive and statistically significant. However, this may simply reflect a pattern where large radio companies own stations which tend to have greater signal coverage and more listeners. The specifications in column (2) includes station-category fixed effects. Following the pair regressions I drop observations from 12 months following a change in both of the local common ownership (own and other) variables. Local common ownership with another station increases listenership by 6% while local common ownership by competitors decreases listenership for an airplay station remaining in the category. Both of these results are consistent with the pair analysis. An increase in own national ownership has no significant effect on station listenership, and, most importantly for the analysis here, controlling for national ownership does not change my conclusions about

Table 9: Mergers and Station Listenership

	(1)	(2)
Specification	No Station-Category Fixed Effects	Station-Category Fixed Effects
Sample	Airplay Stations	Airplay Stations
Drop 12 months following change in local common ownership variables	No	Yes
Dependent variable	Log of station share	Log of station share
Number of airplay stations commonly owned in same market-category	0.0752 (0.0052)***	0.0600 (0.0107)***
Other stations in same market-category commonly owned by other firms (dummy)	0.0139 (0.0135)	-0.0135 (0.0073)*
Log(Number of stations owned in same category nationally)	0.0354 (0.0019)***	-0.0008 (0.0018)
Station-Category Fixed Effects	No	Yes
Control Dummies		
Category Dummies	Yes	No
Quarter Dummies	Yes	Yes
Number of Station Dummies	Yes	Yes
Adjusted R-squared	0.2545	0.0869
Number of Observations	8,202	7,829

Notes: see Table 4. Driscoll-Kraay standard errors in parentheses allowing for correlation across panels (station-categories) and one year (two quarters in my data) of time-series correlation.

the effects of local common ownership.[35]

Changes in Commercial Loads as an Alternative Explanation for the Redistribution of Listeners. The observed changes in positioning provide a consistent explanation for the redistribution of listeners across stations, but changes in prices provide an alternative explanation. In particular, if the merging parties exercise greater market power in the advertising market then they may cut commercial loads (prices) and attract listeners. I now show that there is no evidence for this type of change.

The airplay log shown in Table 1 lists when a commercial break is played between songs. Unfortunately, most of the logs from 1998 and 1999 do not list commercial breaks, although there is some commercial data for 709 stations in these years. The vast majority of the logs from 2000 and 2001 do list commercials. I use two measures of a station's commercial load in an hour. The first measure is simply a count of how many breaks are indicated in a log. The second measure is an estimate of how many minutes of commercials are played during an hour, based on the time between songs when a break is indicated.[36] There is more scope for mismeasurement when there is a lot of non-music programming, which is common during the morning drivetime period, and radio listening is low during the evening and at night (Arbitron (2005)). I therefore only use hours between 10 am and 7 pm and drop station-hours with less than 8 songs.[37] This gives a sample of 53,955 station-hours with commercial information in 1998, 41,050 in 1999, 408,643 in 2000 and 456,986 in 2001. The average number of commercial breaks per hour is 2.2 (standard deviation 0.78) with 24,840 commercial-free hours. The most common arrangements are 2 commercial breaks (562,043 station-hours) and 3 breaks (238,518 station-hours). The estimated average number of commercial minutes per hour is 11.95 (standard deviation 4.69). This is consistent with an industry estimate that music stations were playing 12

[35] If station time trends are also included in the regression the coefficient on local common ownership is 0.0975 (0.0452) and the coefficient on national common ownership is -0.0141 (0.0080).

[36] The first step in this procedure is the estimation of the length of each song. This is done using the median number of minutes between the start time of the song and the start time of the next song where no commercial breaks are indicated. The gap between songs is calculated assuming that the song is played its full length. The results are very similar if one imposes restrictions on the maximum length of a break by assuming, for example, that no break has more than six minutes of commercials.

[37] Less than 2% of station-hours have less than 8 songs between 10 am and 7 pm, and the results are not affected if these hours are used as well.

minutes of commercials per hour in 2000.[38]

I analyze the number of commercials using regressions where observations are station-day-hours, rather than pairs, to control for the possible effects of national ownership. The linear specification is

$$c_{idh} = X_{idh}\beta_1 + C_{idh}\beta_2 + N_{idh}\beta_3 + T_{idh}\beta_4 + \varepsilon_{idh} \quad (3)$$

where c_{idh} is the number of commercials which station i has on day d in hour h. C and N are dummies for the station's category and the number of stations in its market-category. T are dummies for the hour, month, day of week and year. X contains the same ownership variables which were used for the station-level listening regressions in Table 9. I calculate Driscoll-Kraay (1998) standard errors which allow for correlations across panel (station-hours) and I specify that there may be up to 60 days (2 months) of time series correlation.

Table 10 reports the results. The specifications in columns (1) and (2) use the number of minutes of commercials as the dependent variable. The column (1) coefficients indicate that common ownership with an additional station in a local market-category is associated with playing 24 seconds more commercials per hour (4%), while national common ownership is also associated with an increase in commercial loads. Stations competing locally with commonly owned stations tend to play fewer commercials.

Column (2) includes station-category-hour fixed effects. Both of the within-market ownership coefficients are now small and statistically insignificant, so that there is no evidence that mergers change the loads of either the merging parties or competitors. This is also true if one drops the 12 months following the change in ownership, although it is standard to assume that firms can adjust prices (loads) more quickly than they can adjust the positioning of their products. National common ownership does appear to be associated with increases in how many commercials are played. Column (3) uses the number of blocks as the dependent variable. I estimate a conditional fixed effects Poisson

[38] Radio and Records (April 21, 2000) quoted by SchardtMedia's "Listener Choice Radio Study", http://www.listenerchoice.com/research/RS2000.html.

Table 10: Mergers and Commercial Loads

	(1)			(2)			(3)	
Specification	No Station-Category-Hour Fixed Effects			Station-Category-Hour Fixed Effects			Station-Category-Hour Fixed Effects Conditional Poisson Model	
Sample	Airplay Station Hours 10am-7pm with at Least 8 songs			Airplay Station Hours 10am-7pm with at Least 8 songs			Airplay Station Hours 10am-7pm with at Least 8 songs	
Dependent Variable	Number of minutes of commercials in hour			Number of minutes of commercials in hour			Number of breaks in hour	
Number of airplay stations commonly owned in same market-category	0.3811	(0.1126)	***	-0.0150	(0.1035)		0.0008	(0.0173)
Other stations in same market-category co owned by other firms (dummy)	-0.4810	(0.1111)	***	-0.1649	(0.1541)		0.0002	(0.0245)
Log(Number of stations owned in same category nationally)	0.2912	(0.0199)	***	0.1530	(0.0385)	***	0.0059	(0.0070)
Station-Category-Hour Fixed Effects	No			Yes			Yes	
<u>Control Dummies</u>								
Category Dummies	Yes			No			No	
Hour, Day of Week, Month, Year	Yes			Yes			Yes	
Number of Stations Dummies	Yes			Yes			Yes	
Adjusted R-squared	0.1069			0.0829			-	
Log likelihood	-			-			-1,318,669.9	
Number of observations	960,634			960,634			960,634	

<u>Notes:</u> see Table 4. Driscoll-Kraay standard errors in parentheses in columns (1) & (2) allowing for correlation across panels (station-category-hours) and 60 days of time-series correlation. Standard errors in column (3) calculated using a resampling bootstrap with 50 repetitions clustered on the market.

model (Hausman et al. (1984)) as the number of blocks is small and discrete. Once again, within market common ownership appears to have very small effects on commercial loads, indicating they cannot explain the changes in listenership.

These quantity results are consistent with the findings of research which has used data on market-level average advertising prices. Brown and Williams (2002) find that changes in local market concentration had no effect on advertising prices between 1996 and 2001.[39] Consistent with the column (2) results, Brown and Williams also find that a greater presence of national radio firms is associated with lower advertising prices.

6 Conclusion

This paper has shown that mergers in the commercial music radio industry lead to important changes in product positioning. Common owners of stations in the same broad music category reposition their stations so that they are more differentiated from each other, while making them more like competitors. Consistent with these changes, listeners are redistributed across stations with the merging parties gaining listeners and competitors losing them. Price effects do not appear to be important, while there is some evidence that the increased competitive pressure causes competitors to switch programming categories. All of these effects are different from those envisaged in the *Horizontal Merger Guidelines*.

Two issues merit further discussion. The first concerns the implications of the results for welfare and merger policy in the radio industry. Changes in horizontal product positioning without changes in prices will obviously tend to affect different listeners in different ways: consumers who prefer the old programming combinations will have their utility reduced, while those who prefer the new ones will be better off. Without structural estimates of consumer preferences over different types of music we cannot say whether aggregate listener welfare tends to increase or decrease. Unfortunately the identification and estimation of consumer preferences with rich, multidimensional product spaces and

[39] Waldfogel and Wulf (2006) find a similar result looking at changes in average prices around the 1996 Act.

endogenous positioning is beyond the current literature, and it will be particularly difficult when only aggregate station audience data is available. The parties that appear to be harmed by mergers are competing stations, who suffer because of how the merging parties reposition their stations. Competitors who remain in the same category tend to lose listeners while those who leave the category will presumably have to pay some costs when they try to establish themselves in a new category (Sweeting (2007) provides estimates of category switching costs). An open question is how far merger policy should take these effects on competitors into account. When firms only compete in prices or quantities and product locations are fixed, competitors will only tend to be hurt if the merger generates significant efficiencies which is when consumers and total welfare tend to increase (Farrell and Shapiro (1990) analyze the Cournot case). However, this is not necessarily true when repositioning is possible, so it may be necessary to look more closely to what happens to total producer surplus.

The second issue is whether important post-merger changes in positioning are likely to be found in other industries. The ease of repositioning in radio makes it more likely that changes will happen quickly, which is one reason why it is a good industry to look at. However it is plausible that the same incentives for repositioning exist in other industries and may affect positioning decisions when product lines are updated or rebranded. Identifying whether horizontal or vertical repositioning substantially affects the outcome of mergers in other industries is an important direction for future research.

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A Theoretical Effects of Common Ownership

In this Appendix I show how common ownership affects the first-order conditions of station A in the model described in Section 2.[40]

When stations A and B are separately owned, A's first order condition in the second stage of the game is

$$p(\underline{c})L_A(a,\underline{c}) + c_A L_A(a,\underline{c})\frac{\partial p(\underline{c})}{\partial c_A} + c_A p(\underline{c})\frac{\partial L_A(a,\underline{c})}{\partial c_A} = 0 \tag{4}$$

The second and third terms reflect how increasing commercial loads may reduce the price of advertising if $\frac{\partial p(\underline{c})}{\partial c_A} < 0$ or reduce A's listenership if listeners dislike commercials $\left(\frac{\partial L_A(a,\underline{c})}{\partial c_A} < 0\right)$. When A and B are commonly owned, A's first order condition is

$$p(\underline{c})L_A(a,\underline{c}) + \sum_{j=A,B} c_j L_j(a,\underline{c})\frac{\partial p(\underline{c})}{\partial c_A} + c_j p(\underline{c})\frac{\partial L_j(a,\underline{c})}{\partial c_A} = 0 \tag{5}$$

The additional terms reflect how A's commercial load affects B's revenues. Common ownership gives A an additional incentive to increase its commercial load if $\frac{\partial L_B(a,\underline{c})}{\partial c_A} > 0$ (the standard multi-product pricing effect for substitutes) and an additional incentive to reduce its load if $\frac{\partial p(\underline{c})}{\partial c_A} < 0$ (a market power effect in the market for advertisers).

In the first stage of the game A chooses its location. To limit the amount of notation, define $\Pi_A(a) = c_A^*(a)p(\underline{c}^*(a))L_A(a,\underline{c}^*(a))$ where $\underline{c}^*(a)$ are the equilibrium commercial loads in the second stage. The envelope theorem implies that $\frac{\partial \Pi_A}{\partial c_A} = 0$. A's first order condition when all stations are separately owned is

$$\frac{d\Pi_A}{da} = \underbrace{\frac{\partial \Pi_A}{\partial L_A}\frac{\partial L_A}{\partial a}}_{\text{Direct effect}} + \underbrace{\frac{\partial \Pi_A}{\partial L_A}\left(\frac{\partial L_A}{\partial c_B}\frac{dc_B^*}{da} + \frac{\partial L_A}{\partial c_C}\frac{dc_C^*}{da}\right)}_{\text{Strategic effect 1 through A's listenership}} + \underbrace{\frac{\partial \Pi_A}{\partial p}\left(\frac{\partial p}{\partial c_B}\frac{dc_B^*}{da} + \frac{\partial p}{\partial c_C}\frac{dc_C^*}{da}\right)}_{\text{Strategic effect 2 through price of advertising}} = 0 \tag{6}$$

The direct effect reflects how changing a affects the distance that listeners have to travel to A. When a increases, all else equal, some listeners will switch from A to B, and others will switch from C to A. The second term reflects how the choice of a affects other stations' choices of commercial loads and how this changes A's listenership. The standard effect is that A has an incentive to strategically differentiate its location from B and C to soften competition, increasing their commercial loads, because this tends to increase A's listenership. The third term reflects how the choice of a affects other stations' choices of commercial loads and how this changes the price of commercials. If the price falls when other stations play more commercials then A may want to toughen second stage competition to increase advertising prices.

When A and B are commonly owned a is chosen to maximize $\Pi_{A\&B}(a) = c_A^*(a)p(\underline{c}^*(a))L_A(a,\underline{c}^*(a)) + c_B^*(a)p(\underline{c}^*(a))L_B(a,\underline{c}^*(a))$. The envelope theorem implies that both $\frac{\partial \Pi_{A\&B}}{\partial c_A} = 0$ and $\frac{\partial \Pi_{A\&B}}{\partial c_B} = 0$. The

[40] The assumption that station choices will satisfy first-order conditions does not hold in many simple models of firm location. For example, a two-stage circular city model with separately owned firms, a uniform distribution of consumers and linear transport costs has no subgame perfect equilibrium (Economides (1989)).

first order condition with respect to a is

$$\frac{d\Pi_{A\&B}}{da} = \underbrace{\frac{\partial \Pi_{A\&B}}{\partial L_A}\frac{\partial L_A}{\partial a} + \frac{\partial \Pi_{A\&B}}{\partial L_B}\frac{\partial L_B}{\partial a}}_{\text{Direct effect}} + \underbrace{\left(\frac{\partial \Pi_{A\&B}}{\partial L_A}\frac{\partial L_A}{\partial c_C} + \frac{\partial \Pi_{A\&B}}{\partial L_B}\frac{\partial L_B}{\partial c_C}\right)\frac{dc_C^*}{da}}_{\text{Strategic effect 1 through A and B's listenership}} + \underbrace{\frac{\partial \Pi_{A\&B}}{\partial p}\frac{\partial p}{\partial c_C}\frac{dc_C^*}{da}}_{\text{Strategic effect 2 through price of advertising}} = 0 \tag{7}$$

The change in the direct effect provides a common owner with an incentive to increase a, so that A takes listeners from C rather than cannibalizing B's audience. The change in the strategic effects is that, because A and B set commercial loads cooperatively in the second stage, A only has an incentive to affect C's choice through a strategic choice of A. If reducing a softens competition and an increase in C's commercial load increases A and B's profits then the strategic effects will tend to move A away from C and towards B because A no longer benefits from strategically differentiating itself from B.

B Projection of Artists and Stations into Two Dimensional Music Product Space

This Appendix describes the construction of Figures 2(a) and (b). Artists and Adult Contemporary category stations are projected into a two dimensional music space using station playlists from the first week of November 2001. The procedure is:

1. artists are located in a high dimensional space where each station is an orthogonal dimension of the space. An artist's location reflects the proportion of its plays coming from each station. For example, if there were three stations and an artist was 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. the distances between each of the 60 most played artists (who account for 47% of the songs played by all of the stations in the category) are measured by the angle (in radians) between their location vectors;

3. the 60 most played artists are projected into the plane minimizing the difference between the distances between the artists in the plane and the distances between them in the high-dimensional space. The objective function is

$$\sum_{i=1}^{59}\sum_{j=i+1}^{60}\left(d_{ij} - \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}\right)^2 \tag{8}$$

   where d_{ij} is the high-dimensional distance between artists i and j found in step 2 and (x_i, y_i) are the coordinates of artist i in the plane. These are the parameters to be estimated. The most played artist is fixed at the origin and the second most played artist is fixed on the x-axis. (8) may have multiple local minima so the minimization is repeated from 100 different sets of starting values. 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;

4. the distance between the 61^{st} most played artist and each of the 60 most played artists in the high dimensional space is measured. The 61^{st} most played artist is then located by minimizing

$\sum_{j=1}^{60}\left(d_{61j} - \sqrt{(x_{61} - x_j)^2 + (y_{61} - y_j)^2}\right)$ where the locations of the 60 most played artists are fixed. A single starting point, at the average coordinates of the artists already located, is used. This procedure is repeated for each subsequent artist, taking the location of all of the more heavily played artists as given; and,

5. each station is located at the weighted average of the coordinates of the artists which it plays, with the weights equal to the share of each artist in its playlist.