The Timing of Commercial Breaks and Music Variety in the Radio Industry

by

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Abstract

This thesis contains three empirical essays using a new panel dataset of airplay on contemporary music radio stations. The first and third essays examine the timing of commercial breaks. Stations tend to play their commercials at the same time but it is unclear whether this is due to stations wanting to coordinate on timing, to reduce the avoidance of commercials, rather than common factors which simply make some times better for commercials. The first essay models timing decisions as an imperfect information coordination game. The game has multiple equilibria, in which stations coordinate but on different times, if the incentive to coordinate is strong enough. The essay shows how the existence of multiple equilibria, both in the game and in the data, can help to identify the parameters of the game and how to test for multiple equilibria. There is evidence of multiple equilibria, allowing the incentive to coordinate to be identified, during drivetime hours. The implied degree of coordination in Nash equilibrium is relatively modest but, because of externalities in the coordination game, the estimates also imply that coordination would be almost perfect if stations maximized their joint payoffs. The third essay uses a set of simple models to show that, if stations want to choose either the same or different times for commercials, the degree to which commercials overlap should depend on market characteristics such as the number of stations and the degree of common station ownership. The majority of the evidence supports models in which, on average, stations want to choose the same time for commercials as other stations in their market. The second essay examines how changes in radio station ownership have affected music variety and finds that a common owner of stations in the same local radio market and the same music category significantly increases the degree of differentiation between these stations, consistent with a model in which common owners internalize "business stealing" effects. Common ownership of stations in the same music category but different local markets results in, at most, a small degree of playlist homogenization. Panel data on station listenership provides further support for the business stealing explanation, as when stations in a local market become commonly owned their audiences tend to increase.

Thesis Supervisor: Glenn D. Ellison
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All three essays in this thesis use a dataset of airplay on contemporary music radio stations to which I was given access by Rich Meyer of Mediabase 24/7. The National Association of Broadcasters provided me with a research grant to buy a year's subscription to BIAfn's *Media Access Pro* database and invited me to present an earlier version of the first essay at the NAB/BEA convention in Las Vegas in April 2003. I am also grateful to the Kennedy Memorial Trust for funding my first year at MIT.

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Contents

Chapter 1

Introduction

This thesis contains three empirical essays which examine product choices in the contemporary music radio industry. In particular they look at two choices, the timing of commercial breaks and song selection, which are relatively easy for station programmers to change from day-to-day or week-to-week. This provides an unusually nice setting for examining the economics of how firms select product characteristics because it is reasonable to assume that these characteristics are chosen optimally given a station's current environment. In addition we can observe how station choices respond to changes in their environment, such as changes in station ownership which were common in the late 1990s, as well as differences in their environment which are relatively fixed over time but vary across markets, such as market size and the proximity of nearby markets. I study music radio because detailed data is available: all of the essays use a new dataset which provides minute-by-minute information on what is being played for almost 1,100 contemporary music radio stations in 148 different metro-markets.

The first and third essays study the timing of commercial breaks. They are motivated by the striking empirical fact that stations tend to play commercials at the same time: for example, throughout the day there are over 15 times as many stations playing commercials five minutes before the hour than five minutes after the hour. The question is whether this pattern reflects stations trying to choose the same times for commercials as other stations rather than common factors which make some minutes in each hour more attractive for commercials for each station independent of what other stations are doing. It is plausible that stations want to play their commercials at the same time because their business consists of selling the audience of commercials to advertisers who value people listening to the commercials while many listeners try to avoid listening to commercials by searching for music on other stations. If stations play commercials at the same time, then the avoidance of commercials may be reduced. On the other hand, there is also evidence that common factors, such as the way in which Arbitron estimates radio ratings, can explain why some parts of the hour have more commercials than others. The first and third essays present alternative approaches for identifying whether coordination or common factors are important using different features of the data. The question of how the separate roles of common factors and strategic interactions can be identified also arises in many other economic settings. For example, the geographic clustering of firms in an industry could be explained by the existence of either benefits to agglomeration or particular geographic areas having characteristics which make them particularly attractive to all firms independent of whether other firms choose to locate there. Similarly, if consumers make the same choice this may or may not be explained by the existence of demand externalities or peer effects.

The first essay models the timing decision as a simple coordination game in which each station may have an incentive to choose the same times as other stations in its market, together with a common preference for particular times which is shared by other stations and some individual idiosyncratic preferences. The game has multiple equilibria, with stations coordinating but on different times in different equilibria, if and only if the incentive to coordinate is strong enough. I show how, under the assumption that common factors are the same across markets, it is possible to use the existence of multiple equilibria in the data, with different markets coordinating on different times, to identify the strength of the incentive to coordinate and the role of common factors. The idea of using multiple equilibria to help with identification contrasts with previous work on the estimation of games, such as entry games, in which multiple equilibria have been viewed as only creating econometric problems. I also show how to test for multiple equilibria. I estimate a number of simple models using data from the last quarter of the hour, the part with the most commercials, and find evidence of multiple equilibria, allowing the incentive to coordinate to be identified, during drivetime but not outside drivetime. This is consistent with the fact that there are only multiple equilibria when the incentive to coordinate is strong enough because this incentive should be stronger during drivetime when more listeners are known to switch stations. However, even during drivetime the degree of coordination in

Nash equilibrium is relatively modest. This may be explained by the existence of externalities in the coordination game where a station does not take into account how its timing decisions affect the audience of commercials on other stations. The estimates predict that if stations did internalize the externalities the degree of coordination would be almost perfect.

The approach in the third essay does not necessarily require that the common factors are the same across markets. I show that if the observed imperfect overlap of commercials is an equilibrium outcome of a timing game in which stations want to coordinate on timing then we would expect the observed overlap to vary in sensible ways with market characteristics such as the number of stations in the market and the degree of common ownership. Similarly if stations want to choose different times for commercial breaks, which could be justified by certain formulations of listener behavior, then we would also expect these characteristics to matter but in opposite directions. On the other hand, if only common factors affect timing decisions we would not expect these characteristics to matter as long as the relative importance of common factors across markets is not correlated with these characteristics and changes in these characteristics within markets over time. The majority of the empirical results, particularly outside of the largest markets, are consistent with a theory in which stations want to choose the same times for commercials.

The second essay uses data on the identity of songs and artists which stations play to examine the relationship between station ownership and music variety. The effect of common ownership on what is heard on radio has been the subject of recent popular controversy. In many metro-markets, more than one station in the same music category has become owned by the same firm since the relaxation of ownership restrictions in the 1996 Telecommunications Act. Theory provides ambiguous predictions about whether these stations should differentiate more or less than separately owned stations and previous empirical work, for example Berry and Waldfogel (2001), Williams et al. (2002) and Chambers (2003), has reached contradictory conclusions. I study the effect of actual changes in station ownership using a much more detailed panel dataset on the music that stations play than has been used before. I find that common ownership of stations in the same metro-market and in the same music category is associated with significant increases in differentiation. The effect is quite large in size and holds for a number of different ways of using the data to place stations in music space. I also examine the effect of common ownership of stations in different metro-markets where a common owner might be expected to homogenize airplay. I find evidence of only very limited homogenization. In order to understand how the changes in product positioning affect listener welfare I examine how changes in station ownership affect station listenership, finding evidence that when stations in the same metro-market and music category become commonly owned their listenership tends to increase. This suggests that common ownership of stations within markets has probably increased listener welfare as well as music variety.

Chapter 2

Coordination Games, Multiple Equilibria and the Timing of Radio Commercials

2.1 Introduction

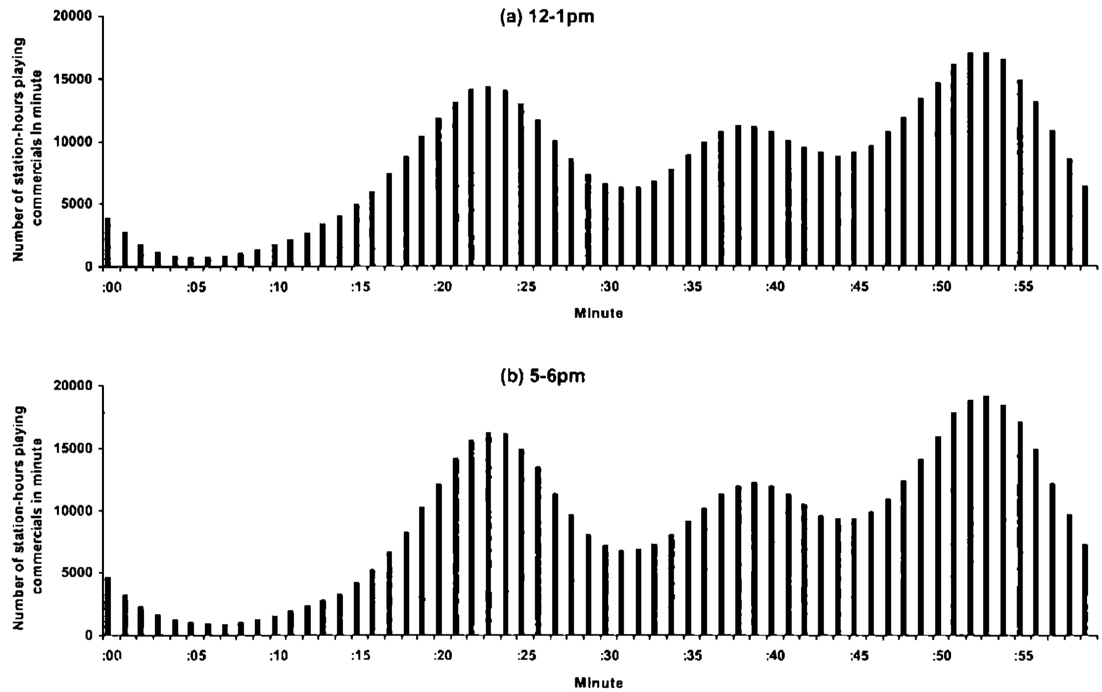
Economists often seek to identify how much an individual agent's choice of action is affected by interactions with other agents making similar choices. For example, Glaeser et al. (1996) examine the role of peer effects on the decision to commit crime, Duflo and Saez (2002) consider the influence of colleagues' decision on an individual's choice of retirement plan, Ellison and Glaeser (1997) study how the benefits of agglomeration affect the geographic location of industries and Goolsbee and Klenow (1999) analyze how network externalities affect the adoption of home computers. This kind of study faces the difficulty that unobservables, rather than interactions between agents, could explain why agents tend to make similar choices. For example, the location of many technology firms in Silicon Valley may be explained either by the existence of significant advantages to agglomeration or by the area having particular natural advantages which would make individual firms want to locate there even if other firms did not.

This paper develops and illustrates one particular approach to this problem. Many economic models in which interactions are important have multiple equilibria. For example, if the advantages of agglomeration are large then a model of firm location decisions may have multiple equilibria in which firms concentrate in different locations. I present a model of a simple imperfect information coordination game with two choices. The game has a maximum of two stable equilibria. I show how the existence of multiple equilibria, both in the model and in data from multiple independent repetitions of the game, can be used to identify the parameters of the game including the incentive which players have to coordinate. To be precise, I give the conditions under which two distinct sets of equilibrium strategies can be identified from the data and show that any two distinct sets of equilibrium strategies can only be supported by a unique set of parameters. On the other hand, if there is only one equilibrium in the game then the parameters cannot be separately identified. The intuition for these results can easily be seen in the technology firm location example. Suppose that we were able to observe 1,000 independent repetitions of firms taking their location decisions with the natural advantages of each location, independent of any interactions between firms, constant across the repetitions. If technology firms are always clustered in the same locations, such as Silicon Valley, then it clearly remains very hard for us to tell whether agglomeration or natural advantages are more important. On the other hand, if the firms are always clustered but the clusters occur in different locations then this provides evidence that agglomeration is important.

This approach to identification creates a need to be able to test for multiple equilibria. In this setting, the likelihood ratio test statistic (LRTS) does not have its standard χ^2 distribution because some of the parameters are not identified under the null hypothesis of a single equilibrium. I use results on the asymptotic distribution of the LRTS, derived in the literature on testing for genetic linkage, to justify the use of a parametric bootstrap for the LRTS.

I apply this framework using new data on the timing of commercial breaks by contemporary music radio stations. I construct the dataset using a panel of minute-by-minute airplay logs from 1,063 stations based in 146 US local radio markets. Figure 2-1 shows histograms of the number of stations playing commercials each minute during the hours 12-1pm and 5-6pm for almost 50,000 station-hours. The distribution of commercials across minutes is far from uniform with minutes :50-:55 having over 15 times as many commercials as minutes :05-:10 in both of these hours. This pattern is repeated in other hours. The obvious question is: how much of this pattern is due to stations wanting to choose the same times for commercials

Figure 2-1: Histograms of the Number of Stations Playing Commercials Each Minute 12-1pm and 5-6pm



Note: based on airplay data (described in Section 6.1) from 1,063 contemporary music stations in 146 metro-markets. 12-1pm histogram based on 48,889 station-hours with commercials at some point in hour, 5-6pm histogram based on 48,567 station-hours with commercials at some point in hour.

as other stations? The economic rationale for an incentive to coordinate (choose the same times) is quite simple. The business of a commercial station is to sell the audience of its commercial breaks to advertisers. However, a large proportion of listeners switch stations during commercial breaks in search of non-commercial programming on other stations. If a station plays its commercials at the same time as other stations in its market then the ability of its listeners to avoid commercials is reduced and the value of its commercial time to advertisers is correspondingly increased. Advertisers understand this logic. For example, Brydon (1994), an advertising consultant writing about advertising on music radio, argues that "for advertisers, the key point is this: if, at the touch of a button, you can continue to listen to that [music] for which you tuned in, why should you listen to something which is imposing itself upon you, namely a commercial break?". He suggests two possible strategies stations could use to increase the audience of commercials: commercial breaks could be very short or stations could "transmit breaks at universally agreed, uniform times. Why tune to other stations if it's certain that they will be broadcasting commercials as well?".

On the other hand, the two most obvious features of the distributions in Figure 2-1 are that relatively few stations play commercials in the first quarter of each hour and that fewer stations have commercials on the quarter-hour points (:00, :15, :30, :45) than during the surrounding minutes. These features can be explained without direct reference to the incentive to coordinate. First, the largest number of new listeners switch on during the first quarter of each hour and listeners are believed to particularly dislike hearing commercials when they first tune-in.[1] Second, Arbitron's method for estimating station ratings using listener diaries makes it particularly desirable for a station to keep its listeners over the quarter-hour points. A listener counts as a quarter-hour listener for a station if she records herself as listening to the station for at least 5 minutes during the quarter-hour so that if she records that she listened from 4:10 to 4:20 she counts as a listener for both the 4:00-4:15 and the 4:15-4:30 quarter-hours. In order to keep as many listeners as possible most music stations "sweep" the quarter-hours with music which most listeners prefer to commercials (Warren (2001), p. 23-24). Of course, it may be more important for a station to adopt these strategies when other local stations are also using them.

The approach in this paper is to estimate a simple timing game using the possibility that there are multiple equilibria, with stations in different local markets coordinating on having their commercials at slightly different times (for example, Boston stations at 5:50pm and Los Angeles stations at 5:55pm), to identify the strength of the incentive to coordinate. An assumption of this approach is that the natural attractiveness of different minutes for commercials is the same across markets because, for example, Arbitron uses the same method to estimate station ratings in every market. An additional feature of the industry provides a neat check on the results. The timing game only supports multiple equilibria if the incentive to coordinate is sufficiently strong (i.e., a small incentive to coordinate is not enough). Listener switching to avoid commercials, which is the source of the incentive to coordinate, is much more prevalent during the parts of the day known as "drivetime" because more listeners are in their cars and it is easier for

[1] Keith (2000), p. 96. The last quarter of each hour also has the least new tune-ins and the most commercials.

in-car listeners to switch stations. For example, a 1994 Paragon Research survey found that 70% of in-car listeners switch at some point during a commercial break compared with 41% and 29% of at-home and at-work listeners respectively.[2] Consistent with a strong incentive to coordinate creating multiple equilibria, I only find consistent and statistically significant evidence of multiple equilibria during drivetime.

Although I am able to use multiple equilibria to identify the incentive to coordinate during drivetime, the estimates imply that this incentive has relatively modest effects on Nash equilibrium strategies (equivalently, much of the pattern in Figure 2-1 is due to factors other than coordination). This may partly reflect an important feature of the economics of coordination. In Nash equilibrium, an independent station considers its own costs and benefits from coordinating with other local stations but it does not consider how its timing decision affects the commercial audience of other stations. I show that the estimated parameters imply that coordination would be almost perfect if stations maximized their expected joint payoffs. Further interesting empirical results are that I find less coordination in the largest markets and some weak evidence that if many listeners are able to choose between stations from two different markets, then stations in those markets tend to choose the same times for commercial breaks.

The remaining section of this introduction explains the relationship between this paper and the existing literatures on the identification of social interactions and the estimation of games with multiple equilibria. Section 2.2 presents the model of an imperfect information coordination game. Section 2.3 provides the identification results. Sections 2.4 and 2.5 deal with testing and estimation. Section 2.6 presents the application. I estimate the model of Section 2.2 and some more complicated models to investigate particular aspects of the data. Section 2.7 concludes.

[2]Paragon study discussed in MacFarland (1997), p. 89. Arbitron/Edison Media Research (1999) report very similar results. McDowell and Dick (2003) find that in-car listeners switch stations primarily because of commercials. Abernethy (1991) used in-car tape recorders to monitor the behavior of 100 listeners and found that, on average, they switched over 29 times during an hour and avoided over 50% of the commercials they would hear if they listened to just one station. In Fall 2001 39.2% of listening was in-car during weekday drivetimes (6am-10am, 3pm-7pm) compared with 27.4% 10am-3pm and 25% 7pm-midnight (based on data from the Listening Trends section of Arbitron's website, www.arbitron.com).

2.1.1 Relationship to the Existing Literature on the Identification of Social Interactions and the Estimation of Games with Multiple Equilibria

This paper contributes to two distinct literatures. The first literature, which I have already mentioned, is concerned with the identification of social interactions. Empirical research in this area (for example, Duflo and Saez's (2002) analysis of retirement plan choices within departments of academic institutions) has used the fact that agents in well-defined groups are disproportionately likely to make similar choices to provide evidence of social interactions or social learning. However, these patterns have not been treated as representing multiple equilibria in an underlying model so that the role that multiple equilibria can play in identification has not been explored. Manski (1993) and Brock and Durlauf (2001) briefly note the theoretical possibility that multiple equilibria could help to identify social interactions but I believe that my paper is the first to fully work out and apply this logic.

The second related literature has explicitly considered how to estimate models with multiple equilibria, primarily in the context of models of market entry by firms. In an entry model, if firm profits decline with the number of entrants, there are typically multiple equilibria in which different firms enter. This has been seen as creating a problem for estimation because the probability of some observable outcomes are given by inequalities rather than equalities. The typical solution in applied work on static entry games has been to avoid the problem by either using a prediction of the game which is unique (e.g., the number of entrants, Bresnahan and Reiss (1991)) or structuring the game to create a unique equilibrium (e.g., sequential entry, Berry (1992)). Recent papers by Tamer (2002, 2003) and Andrews and Berry (2003) show how to use inequalities for the probabilities of some outcomes to improve efficiency or to identify and estimate ranges of parameters. Tamer (2002) provides an application of this technique to entry by airlines into city-pair markets. Similar issues arise in the estimation of dynamic entry games (for example, Aguirregabiria and Mira (2002), Bajari et al. (2003), Pakes et al. (2003), Pesendorfer and Schmidt-Dengler (2003)). Alternative approaches in this literature have been either to make assumptions which guarantee uniqueness (e.g., Pakes et al.) or to use estimation approaches which require that there is a single equilibrium in the data (e.g., Aguirregabiria and Mira). The contribution of the current paper to this literature is to show how the existence of multiple equilibria, in a model and in the data, could actually help to identify the parameters of interest by ruling out sets of parameters which cannot support all of the observed equilibria. I also consider how to test for multiple equilibria and provide a new empirical application in which it is plausible that multiple equilibria, with radio stations in different markets coordinating on playing commercials at different times, could be observed.

2.2 Model of an Imperfect Information Coordination Game

Consider a simple game in which players choose one of two actions (1 and 2). In the application these will be different times for commercial breaks. Each player i has the following reduced form payoff function from choosing action t

$$\pi_{it} = \beta_t + \alpha P_{-it} + \varepsilon_{it} \tag{2.1}$$

where P_{-it} is the proportion of players other than i choosing action t. The β_ts allow one action to have, on average, a higher payoff for reasons not connected with coordination. α reflects the strength of the incentive to coordinate and I assume $\alpha \geq 0$. If $\alpha = 0$ each player's payoff is independent of other players choices. If $\alpha > 0$ payoffs increase with the proportion of other players who choose the same action. ε_{it} is an idiosyncratic error which is private information to player i. ε_{it} is assumed to be IID across players and it allows players to have different preferences over actions.

i's strategy S_i consists of a rule for selecting its action as a function of $(\varepsilon_{i1}, \varepsilon_{i2})$ and, if $\alpha > 0$, the strategies of the other players (S_{-i}). i's optimal strategy will be to choose action 1 if and only if

$$\beta_1 + \alpha E(P_{-i1}|S_{-i}) + \varepsilon_{i1} \geq \beta_2 + \alpha E(P_{-i2}|S_{-i}) + \varepsilon_{i2} \tag{2.2}$$

I assume that ε has a Type 1 extreme value ("logit") distribution so that the probability that i chooses action 1 when it uses its optimal strategy is

$$p_i^* = \frac{e^{\beta_1 + \alpha E(P_{-i1}|S_{-i})}}{e^{\beta_1 + \alpha E(P_{-i1}|S_{-i})} + e^{\beta_2 + \alpha E(P_{-i2}|S_{-i})}} \tag{2.3}$$

It is straightforward to show that if $\alpha \geq 0$ all Bayesian Nash equilibria will involve players using symmetric strategies.[3] All players choose one action so that in equilibrium $p_i^* = E(P_{-i1}|S_{-i}) = 1 - E(P_{-i2}|S_{-i}) = p^*$. Normalizing β_2 to be zero and relabelling β_1 as β, the equilibrium probability p^* that a player chooses action 1 will satisfy

$$p^* = \frac{e^{\beta+\alpha p^*}}{e^{\beta+\alpha p^*} + e^{\alpha(1-p^*)}} \tag{2.4}$$

The game has multiple equilibria if, for given parameters (β, α), more than one value of p^* satisfies (2.4). Equilibrium strategies are independent of the number of other players because of the assumption that payoffs depend on the proportion of other players choosing action 1.

Figure 2-2(a)-(d) show how player i's reaction function and the equilibria change with β and α. In each diagram the probability that each player other than i chooses action 1 is shown on the horizontal axis and i's probability of choosing action 1 is shown on the vertical axis. There is an equilibrium at any point where the reaction function crosses the 45^0 line. In Figure 2-2(a) $\alpha = 0$ so i's optimal strategy is independent of the strategies of other players and the reaction function is flat. As $\beta > 0$ i's chooses action 1 with higher probability than action 2. In Figure 2-2(b) $\alpha > 0$ so i's payoff from choosing action 1 increases with the probability that other players choose action 1 and the reaction function slopes upwards. The functional form of ε gives the reaction function an S-shape. There is a single equilibrium but, because there is some benefit to coordination, action 1 is chosen with higher probability than in Figure 2-2(a). In Figure 2-2(c) α is higher and the S-shape of the reaction function is more pronounced so that there are three equilibria. The middle equilibrium (slope of the reaction function is greater than 1) is not stable in the sense that use of iterated best responses following a small deviation from equilibrium strategies would not return strategies to the same equilibrium. In the rest of the paper, I will assume that only stable equilibria are played. The S-shape of the reaction function ensures that there are a maximum of two stable equilibria and that one of them will involve players choosing action 1 with probability greater than $\frac{1}{2}$ (I will label this equilibrium A, $p_A^* > \frac{1}{2}$) and that the other will involve players choosing action 1 with probability less than $\frac{1}{2}$

[3]Outline of the proof: suppose that the equilibrium is not symmetric so that player j chooses action 1 with higher probability than player k. In this case $E(P_{-k1}|S_{-k}) - E(P_{-k2}|S_{-k}) > E(P_{-j1}|S_{-j}) - E(P_{-j2}|S_{-j})$ so that from (2.3) k would actually choose action 1 with higher probability than j, a contradiction. Symmetry also applies to games with more than two choices. If $\alpha < 0$ there will be a symmetric equilibrium but there may also be asymmetric equilibria which may give players higher expected payoffs than the symmetric equilibrium.

Figure 2-2: Station Reaction Functions and the Number of Equilibria for Different Values of β and α

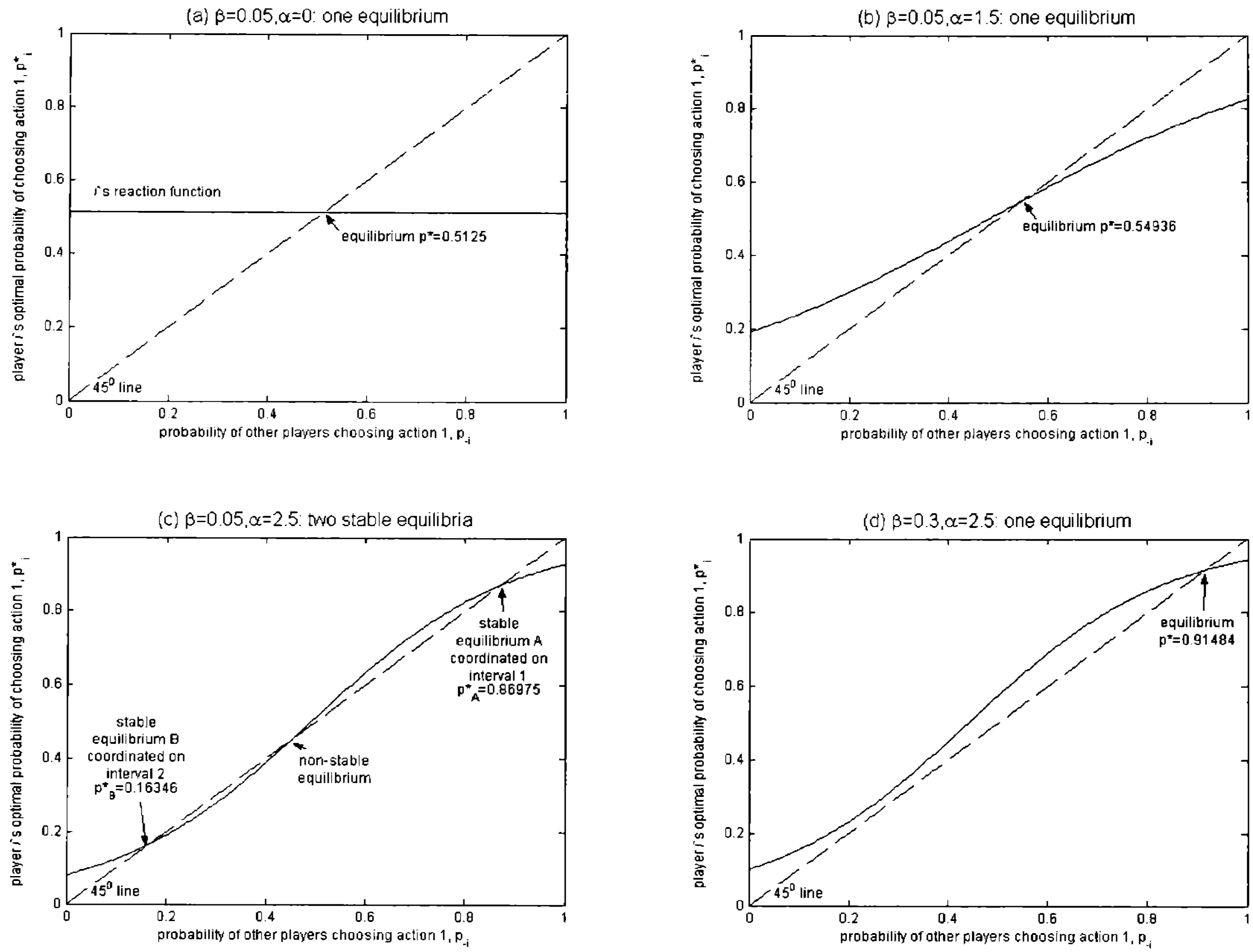
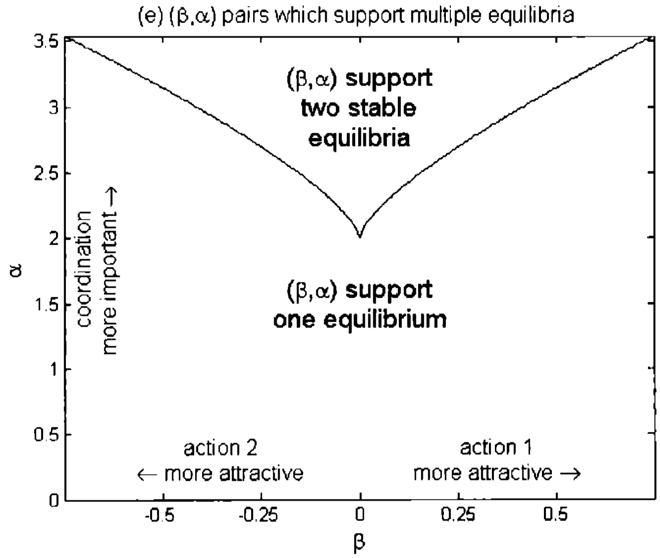


Figure 2-2: continued



(equilibrium B, $p_B^* < \frac{1}{2}$). Players choose the same action with higher probability in equilibrium A than in equilibrium B because $\beta > 0$. In Figure 2-2(d) β increases, the reaction function shifts up and the B (action 2) equilibrium ceases to exist. The intuition for this result is that once action 1 is being chosen by other players with sufficiently high probability an equilibrium involving coordination on action 2 cannot be sustained. Figure 2-2(e) summarizes these results by dividing the (β, α) parameter space into regions which support one equilibrium and two equilibria.[4]

2.2.1 Comparison of Nash Equilibrium and Joint Payoff Maximizing Strategies

If $\alpha > 0$, a player who chooses action 1 increases the payoffs of the other players who choose action 1. In the application, a station which coordinates on timing increases the commercial

[4]In the application, α should be higher during drivetime so it is plausible that we should expect to find more evidence of multiple equilibria during drivetime. We should also not expect to find equilibria in which stations coordinate on having commercials at very unattractive times such as the first quarter of the hour. This seems particularly true given that the timing of commercials involves repeated interaction between the same players so we could expect them to avoid equilibria which involve significantly lower payoffs. For this reason, I study timing choices over two periods at the end of the hour which appear to be the most attractive periods for commercials.

audience of the stations with which it coordinates. This externality means that there is less coordination in Nash equilibrium than there would be if players chose strategies to maximize expected joint payoffs.

Calculating expected joint payoff maximizing strategies is straightforward. I assume that the εs remain private information, so that each player's strategy is only a function of its εs. Suppose that there are N players and that players other than i choose action 1 with probability p_{-i}. If i chooses action 1, an expected $(N-1)p_{-i}$ other players each gain $\frac{\alpha}{N-1}$ so the expected benefit for other players is αp_{-i}. Similarly, if i chooses action 2 the expected benefit is $\alpha(1-p_{-i})$. i maximizes expected joint payoffs by choosing action 1 if and only if

$$\beta + 2\alpha p_{-i} + \varepsilon_{i1} \geq 2\alpha(1-p_{-i}) + \varepsilon_{i2} \tag{2.5}$$

Expected joint payoff maximizing strategies will be symmetric and the probability (p^{JP}) of choosing action 1 will satisfy

$$p^{JP} = \frac{e^{\beta+2\alpha p^{JP}}}{e^{\beta+2\alpha p^{JP}} + e^{2\alpha(1-p^{JP})}} \tag{2.6}$$

More than one value of p^{JP} may satisfy (2.6) but if $\beta > 0$ then coordination will be on action 1. The change in strategies with expected joint payoff maximization can be large partly because, in this game, coordination is a "strategic complement" (Bulow et al. (1985)): an increase in the probability that one player chooses action 1 raises the incentive of every other player to also choose action 1.

2.2.2 Empirical Model and Equilibrium Selection

Suppose that data giving the number of players choosing action 1 (n_1) and the number of players choosing action 2 (n_2) is available for independent repetitions of the game indexed by m (markets in the application). If (β, α) support one equilibrium the probability of an (n_{m1}, n_{m2}) observation is

$$\Pr(n_{m1}, n_{m2}|\beta, \alpha) = \frac{(n_{m1}+n_{m2})!}{n_{m1}!n_{m2}!} p^*(\beta,\alpha)^{n_{m1}}(1-p^*(\beta,\alpha))^{n_{m2}} \tag{2.7}$$

If there are two equilibria and an indicator Z_m^A takes value 1 if repetition m is generated from equilibrium A and 0 if it is generated from equilibrium B, the probability is

$$\Pr(n_{m1}, n_{m2}|\beta, \alpha, Z_m^A) = \frac{(n_{m1}+n_{m2})!}{n_{m1}!n_{m2}!}\left(\begin{array}{c} Z_m^A p_A^*(\beta,\alpha)^{n_{m1}}(1-p_A^*(\beta,\alpha))^{n_{m2}}+ \\ (1-Z_m^A)p_B^*(\beta,\alpha)^{n_{m1}}(1-p_B^*(\beta,\alpha))^{n_{m2}} \end{array}\right) \tag{2.8}$$

This is the "complete data" probability of the observation. Of course, the Z^As are not observed. Therefore assume that the equilibrium A is played with probability λ which is independent of any m characteristics and the εs. This defines a simple "equilibrium selection" mechanism.

$$Z_m^A \sim \text{Bernoulli}(\lambda) \tag{2.9}$$

λ is an incidental parameter of the game.[5] The incomplete data probability is then

$$\Pr(n_{m1}, n_{m2}|\beta, \alpha, \lambda) = \frac{(n_{m1}+n_{m2})!}{n_{m1}!n_{m2}!}\left(\begin{array}{c} \lambda p_A^*(\beta,\alpha))^{n_{m1}}(1-p_A^*(\beta,\alpha))^{n_{m2}}+ \\ (1-\lambda)p_B^*(\beta,\alpha))^{n_{m1}}(1-p_B^*(\beta,\alpha))^{n_{m2}} \end{array}\right) \tag{2.10}$$

(2.10) is the probability of an observation in a binomial mixture model. A mixture model is one in which observations may be drawn from more than one distribution: a switching regression model is an example. Binomial data gives the number of members of a specified group that have a particular property and the number which do not. Here the property is whether players choose action 1. p_A^* and p_B^* are the binomial probabilities of the components of the mixture and λ is the mixing parameter which defines the proportion of observations coming from each component. The next two sections on identification and testing use results from the statistics and genetics literature on binomial mixture models.

2.3 Identification

I now define what I mean by identification and give the conditions on the data generating process (DGP) under which the parameters of interest, β and α, are identified. The main

[5] The use of λ to deal with multiple equilibria is not new. For example, Bjorn and Vuong (1985) and Kooreman (1994) include λ in their models of household labour supply decisions. However these authors *assume* a value of λ (e.g., all equilibria are assumed to be played with equal probability).

results are: (i) if the true β and α support only one equilibrium then they cannot be separately identified i.e., more than one pair of parameters gives the same probability for every observable outcome; and (ii) if the true β and α support two stable equilibria then they can be separately identified if two further conditions on the DGP hold. The first condition is that there must be a strictly positive proportion of observations from each equilibrium. The second condition is that there must be some observations involving at least three players. Under these conditions two equilibrium strategies (p_A^*, p_B^*) can be identified. I show that a (p_A^*, p_B^*) pair with $p_A^* \neq p_B^*$ can only be supported by a unique (β, α) pair so (β, α) can therefore also be identified.

2.3.1 Data Generating Process (DGP)

I begin by summarizing the DGP. The DGP is defined by (2.8) and (2.9) where p_A^* and p_B^* are values of p^* which satisfy (2.4) such that $\frac{\partial\left(\frac{e^{\beta+\alpha p^*}}{e^{\beta+\alpha p^*}+e^{\alpha(1-p^*)}}\right)}{\partial p^*} < 1$ (i.e., they are stable equilibria) and $p_A^* \geq p_B^*$. If only one value of p^* satisfies (2.4) then $p_A^* = p_B^*$ and (2.8) is equivalent to (2.7). The parameter space is (β, α, λ) with $-\infty \leq \beta \leq \infty$, $\alpha \geq 0$ and $0 \leq \lambda \leq 1$. The sample space is the set of possible outcomes (n_{m1}, n_{m2}) from repetitions of the game indexed by $m = 1, ..., M$ with $n_{m1} \geq 0, n_{m2} \geq 0$. I define μ_N as the proportion of observations where $n_{m1} + n_{m2} = N$.

2.3.2 Definition of Identification

I use the following definition of identification for a vector of parameters (β, α, λ).

Definition 1 (Parameter Vector Identification) *A vector of parameters (β, α, λ) is separately identified in this model if and only if for any pair $(\beta', \alpha', \lambda')$,*

$$\Pr(n_{m1}, n_{m2}|\beta, \alpha, \lambda) = \Pr(n_{m1}, n_{m2}|\beta', \alpha', \lambda') \quad \forall n_{m1}, n_{m2} \tag{2.11}$$

implies that $(\beta, \alpha, \lambda) = (\beta', \alpha', \lambda')$.

In standard terminology, the model would be identified if all possible parameter vectors were identified in this sense. My model is not globally identified because parameter vectors which support only one equilibrium are not identified.

2.3.3 Identification Results

Proposition 2 *All parameter vectors (β, α, λ) where (β, α) support only one stable equilibrium are not separately identified.*

Proof. If (β, α) support only one stable equilibrium then the single equilibrium choice probability p^* will satisfy

$$p^*(\beta, \alpha) = \frac{e^{\beta + \alpha p^*}}{e^{\beta + \alpha p^*} + e^{\alpha(1-p^*)}} \tag{2.12}$$

From (2.8) and (2.9) the probability of an (n_{m1}, n_{m2}) observation is

$$\Pr(n_{m1}, n_{m2} | \beta, \alpha, \lambda) = \frac{(n_{m1} + n_{m2})!}{n_{m1}! n_{m2}!} \begin{pmatrix} \lambda p^*(\beta, \alpha)^{n_{m1}} (1 - p^*(\beta, \alpha))^{n_{m2}} + \\ (1 - \lambda) p^*(\beta, \alpha)^{n_{m1}} (1 - p^*(\beta, \alpha))^{n_{m2}} \end{pmatrix} \tag{2.13}$$

It is immediate that λ is not identified and (2.13) simplifies to

$$\Pr(n_{m1}, n_{m2} | \beta, \alpha) = \frac{(n_{m1} + n_{m2})!}{n_{m1}! n_{m2}!} p^*(\beta, \alpha)^{n_{m1}} (1 - p^*(\beta, \alpha))^{n_{m2}} \tag{2.14}$$

I show that (β, α) are not separately identified by naming $(\beta', \alpha') \neq (\beta, \alpha)$ pairs which also support one equilibrium choice probability $p^{*\prime}(\beta', \alpha')$ with $p^{*\prime}(\beta', \alpha') = p^*(\beta, \alpha)$. I do this for two cases, $\alpha > 0$ and $\alpha = 0$. Although I name particular (β', α') pairs, there is a continuum of pairs which would work.

If $\alpha > 0$, consider $\alpha' = 0$ and $\beta' = \beta - \alpha + 2\alpha p^*$. (β', α') will generate equilibrium choice probability $p^{*\prime}$ satisfying

$$p^{*\prime}(\beta', \alpha') = \frac{e^{\beta'}}{1 + e^{\beta'}} = \frac{e^{\beta - \alpha + 2\alpha p^*}}{1 + e^{\beta - \alpha + 2\alpha p^*}} \tag{2.15}$$

The RHS of (2.15) is a constant independent of $p^{*\prime}$ so only one value of $p^{*\prime}$ satisfies (2.15) and there is only one equilibrium supported by (β', α'). (2.15) implies

$$p^{*\prime}(\beta', \alpha') = \frac{e^{\beta + \alpha p^*}}{e^{\beta + \alpha p^*} + e^{\alpha(1-p^*)}} \tag{2.16}$$

so $p^{*\prime}(\beta',\alpha') = p^*(\beta,\alpha)$ and the probability of a (n_{m1}, n_{m2}) observation is

$$\Pr(n_{m1}, n_{m2}|\beta',\alpha') = \frac{(n_{m1}+n_{m2})!}{n_{m1}!n_{m2}!} p^*(\beta,\alpha)^{n_{m1}}(1-p^*(\beta,\alpha))^{n_{m2}} \tag{2.17}$$

Comparing (2.14) and (2.17) shows that (β,α) are not separately identified.

If $\alpha = 0$, p^* is given by

$$p^*(\beta,\alpha) = \frac{e^\beta}{1+e^\beta} \tag{2.18}$$

Consider $\alpha' = 1$ and $\beta' = \beta + 1 - 2p^*$. (β',α') will generate equilibrium choice probabilities $p^{*\prime}$ satisfying

$$p^{*\prime}(\beta',\alpha') = \frac{e^{\beta'+\alpha' p^{*\prime}}}{e^{\beta'+\alpha' p^{*\prime}} + e^{\alpha'(1-p^{*\prime})}} = \frac{e^{\beta+1-2p^*+p^{*\prime}}}{e^{\beta+1-2p^*+p^{*\prime}} + e^{(1-p^{*\prime})}} \tag{2.19}$$

The RHS of (2.19) is not a constant (it is a function of $p^{*\prime}$) so I show that with $\alpha' = 1$ there is only one equilibrium (equivalently, one value of $p^{*\prime}$ which solves (2.19)). A necessary condition for there to be multiple equilibria is that the maximum slope of a station's reaction function is at least 1.[6] With reaction function $R(p) = \frac{e^{\beta+\alpha p}}{e^{\alpha(1-p)}+e^{\beta+\alpha p}}$, the slope of the reaction function is

$$\frac{\partial R(p)}{\partial p} = 2\alpha \left(\frac{e^{\beta+\alpha p}}{e^{\alpha(1-p)} + e^{\beta+\alpha p}} \right) \left(1 - \frac{e^{\beta+\alpha p}}{e^{\alpha(1-p)} + e^{\beta+\alpha p}} \right) \tag{2.20}$$

which has a maximum of $\frac{1}{2}\alpha$ at $R(p) = \frac{1}{2}$. With $\alpha' = 1$, the maximum slope of the reaction function is less than 1.

If $p^{*\prime}(\beta',\alpha') = p^*(\beta,\alpha)$ is the solution to (2.19), (2.19) simplifies to

$$p^{*\prime}(\beta',\alpha') = \frac{e^\beta}{1+e^\beta} \tag{2.21}$$

Comparison of (2.18) and (2.21) verifies that $p^{*\prime} = p^*$ is indeed the solution to (2.19). The probability of an observation is again given by (2.17) and comparison of (2.14) and (2.17) shows that (β,α) are not separately identified. ∎

[6] Recall from Section 2.2 that all equilibria are symmetric so that there is an equilibrium where $R(p) = p$ (the reaction function crosses the 45^0 line). The reaction function is continuous on $[0,1]$. Taken together these facts imply that for there to be two distinct equilibria the slope of the reaction function must be greater than 1 at some point.

Parameter vectors which support two stable equilibria are identified if two additional conditions are satisfied.

Condition 3 *Some observations are generated from each equilibrium, i.e.,* $0 < \lambda < 1$.

Condition 4 *Some observed repetitions of the game have at least three players, i.e.,* $\sum_{j=3}^{\infty} \mu_j > 0$.

Proposition 5 *Parameter vectors* (β, α, λ) *which support two distinct stable equilibria are separately identified if Conditions 3 and 4 hold.*

Proof. If (β, α) support two distinct equilibria the probability of an observation is

$$\Pr(n_{m1}, n_{m2}|\beta, \alpha, \lambda) = \frac{(n_{m1} + n_{m2})!}{n_{m1}!n_{m2}!} \begin{pmatrix} \lambda p_A^*(\beta, \alpha))^{n_{m1}}(1 - p_A^*(\beta, \alpha))^{n_{m2}} + \\ (1 - \lambda)p_B^*(\beta, \alpha))^{n_{m1}}(1 - p_B^*(\beta, \alpha))^{n_{m2}} \end{pmatrix} \tag{2.22}$$

with $p_A^* \neq p_B^*$. I proceed in two stages: first, I apply a well-known result to show that (p_A^*, p_B^*, λ) are separately identified under the stated conditions and second, I show that (β, α) are identified if (p_A^*, p_B^*, λ) are identified.

First stage: (2.22) is the pmf of a binomial mixture distribution with two components. The binomial probabilities for the two components are p_A^* and p_B^*, and the mixing proportion parameter is λ. Proposition 4 of Teicher (1963) and the lemma of Margolin et al. (1989) give sufficient conditions for the parameters of binomial mixtures to be identified. Applying these results, (p_A^*, p_B^*, λ), with $p_A^* \geq p_B^*$, are separately identified if $p_A^* \neq p_B^*$ ((β, α) support more than one equilibrium), $0 < \lambda < 1$ (Condition 3) and some of the observed groups contain at least 3 members (Condition 4). Therefore under the stated conditions (p_A^*, p_B^*, λ) are separately identified.[7]

Second stage: it is sufficient to show that there is a unique (β, α) which can support a pair (p_A^*, p_B^*) with $p_A^* \neq p_B^*$ as equilibrium choice probabilities. Suppose not and that $(\beta', \alpha') \neq (\beta, \alpha)$

[7] These conditions are also necessary. If $p_A^* = p_B^*$ then one cannot identify λ because the two components of the mixture are identical (indeed λ is not really defined). If $\lambda = 0$ then one cannot identify p_A^* (no observations come from this component so there is no information on its binomial probability) and if $\lambda = 1$ then one cannot identify p_B^*. If all groups have only 1 or 2 members then the only possible (n_{m1}, n_{m2}) outcomes are $(2,0)$, $(1,1)$ and $(0,2)$. It is easy to show that there is more than one combination of (p_A^*, p_B^*, λ) which give the same probabilities for these outcomes (the intuition is that as the probabilities sum to 1 there are only two equations and three unknowns).

also supports (p_A^*, p_B^*) with $p_A^* \neq p_B^*$ as equilibrium choice probabilities. From (2.4), four equations must hold

$$p_A^* = \frac{e^{\beta+\alpha p_A^*}}{e^{\beta+\alpha p_A^*} + e^{\alpha(1-p_A^*)}} \qquad p_A^* = \frac{e^{\beta'+\alpha' p_A^*}}{e^{\beta'+\alpha' p_A^*} + e^{\alpha'(1-p_A^*)}} \tag{2.23}$$

$$p_B^* = \frac{e^{\beta+\alpha p_B^*}}{e^{\beta+\alpha p_B^*} + e^{\alpha(1-p_B^*)}} \qquad p_B^* = \frac{e^{\beta'+\alpha' p_B^*}}{e^{\beta'+\alpha' p_B^*} + e^{\alpha'(1-p_B^*)}} \tag{2.24}$$

and manipulating each of these equations gives

$$\ln\left(\frac{p_A^*}{1-p_A^*}\right) = \beta + \alpha(2p_A^* - 1) \qquad \ln\left(\frac{p_A^*}{1-p_A^*}\right) = \beta' + \alpha'(2p_A^* - 1) \tag{2.25}$$

$$\ln\left(\frac{p_B^*}{1-p_B^*}\right) = \beta + \alpha(2p_B^* - 1) \qquad \ln\left(\frac{p_B^*}{1-p_B^*}\right) = \beta' + \alpha'(2p_B^* - 1) \tag{2.26}$$

Combining the equations in (2.25) and (2.26) gives

$$\alpha' - \alpha = \frac{\beta - \beta'}{2p_A^* - 1} \quad \text{and} \quad \alpha' - \alpha = \frac{\beta - \beta'}{2p_B^* - 1} \tag{2.27}$$

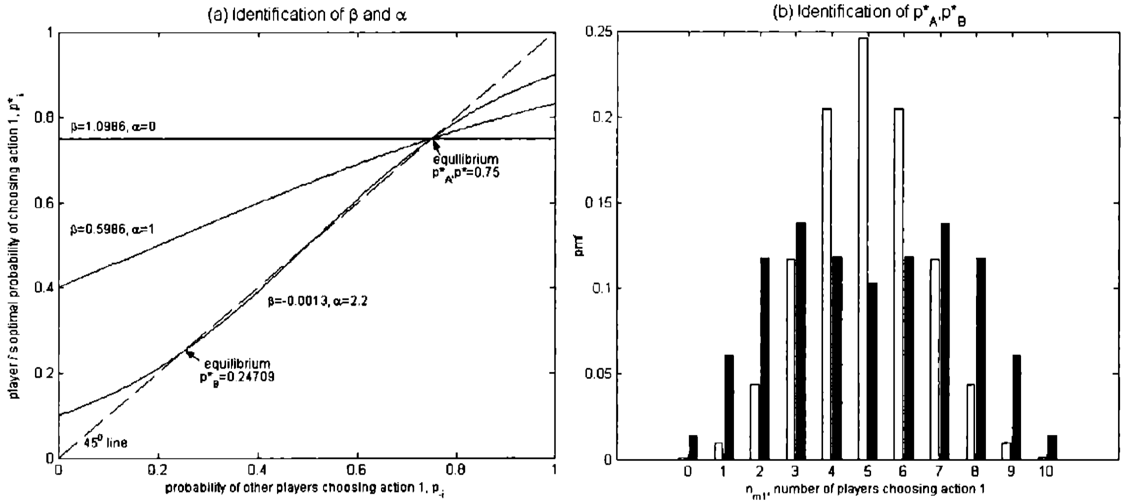
implying $p_A^* = p_B^*$. This contradicts $p_A^* \neq p_B^*$. ■

2.3.4 Comments on Identification

The reaction function diagram in Figure 2-3(a) provides some intuition for the identification results. All of the reaction functions shown are consistent with an equilibrium choice probability of $p^* = 0.75$: if this is the only equilibrium that can be identified in the data then we cannot distinguish between any of these (β, α) pairs. On the other hand, if we can identify $p_A^* = 0.75$ and $p_B^* = 0.24709$ then we can infer that $(\beta = -0.0013, \alpha = 2.2)$ rather than any of the other (β, α) combinations. Figure 2-3(b) illustrates how the equilibrium strategies p_A^* and p_B^* can be identified from the data. Suppose that in all of the repetitions of the game we observe 10 players. The white bars show the pmf of n_{m1} (the number of players choosing action 1) for a single equilibrium $p^* = 0.5$ while the black bars show the pmf for $p_A^* = 0.7$, $p_B^* = 0.3$ and $\lambda = 0.5$. The expected number of players choosing action 1 is the same in each case, but with two equilibria very high or very low values of n_{m1} are observed with higher probability.

The identification results extend to games with more than 2 actions. Suppose that players

Figure 2-3: Identification



choose one of T actions, so that there are $T-1$ β_t parameters and one α parameter. If the true parameters support only one set of equilibrium choice probabilities then $(\beta_1, .., \beta_{T-1}, \alpha)$ cannot be separately identified. On the other hand, the parameters are separately identified if at least two sets of equilibrium choice probabilities can be identified: the number of required equilibria does not increase with the number of actions or parameters.[8] The ability to identify the parameters then depends on being able to consistently identify two or more sets of equilibrium choice probabilities taking into account that a T action game may have more than 2 stable equilibria. This problem would be equivalent to identifying the components of a multinomial mixture model with a possible E_T components where E_T is the maximum number of stable equilibria in the T choice game. Based on the multinomial mixture model results of Kim (1984) and Elmore and Wang (2003) a necessary and sufficient condition would be to have repetitions of the game with $2E_T - 1$ players.

The identification results also extend to cases where (β, α, λ) depend on observed characteristics of the repetition. In Section 2.6.4 I estimate this sort of model to examine whether the incentive to coordinate is lower in larger markets and whether there is any evidence of more

[8]This reflects, at least in part, the logit functional form of ε which leads to the relative choice probabilities of the two actions t and T (with β_T normalized to zero) depending only on the parameters β_t and α. Consequently with two sets of equilibrium choice probabilities one can calculate α and all of the β_ts.

coordination in markets in which more stations are commonly owned. The identification of binomial mixture models where p_A^*, p_B^* and λ depend on characteristics is discussed in Wang (1994). The main addition to the conditions above is that any matrix of regressors must have full rank. If the relationship between p_A^*, p_B^* and λ and the explanatory variables can be identified then the relationship of β and α to the variables can also be worked out. Of course, there can be cases in which not all of the parameters are identified. For example, in the application I allow α and λ to depend on a continuous measure of ownership concentration, HHI_m, and a large market dummy, $LARGE_m$, with β constant across markets. Suppose $\beta > 0$ (action 1 is more attractive), α is increasing in ownership concentration but α is lower in $LARGE_m$ markets so that multiple equilibria cannot be supported in any of the large markets. As long as HHI_m varies across large and small markets and some of the small markets come from each equilibrium, β, the constant and HHI_m coefficients of α and the constant and HHI_m coefficients of λ can be identified from the small markets alone. The $LARGE_m$ coefficient of α can be identified from the how much more coordinated the small markets in equilibrium A are than the large markets (which all coordinate on action 1 because $\beta > 0$). However, as there is only one equilibrium which can be supported in the large markets, the $LARGE_m$ coefficient of λ is not identified.

2.4 Testing for Multiple Equilibria

Testing for multiple equilibria is equivalent to testing whether there are two distinct equilibrium probabilities of choosing action 1 which apply in different repetitions of the game or a single equilibrium choice probability which applies in all repetitions. This is the same problem as testing whether a binomial mixture model has one component or two components. One way to perform this test is to use the likelihood ratio test statistic (LRTS) to compare the likelihood under the null hypothesis of a single component with the likelihood under the alternative hypothesis of two components. However, the LRTS does not have its classic χ^2 distribution when it is used to test for the homogeneity of mixtures. Two features of the problem violate the standard regularity conditions: under the null some of the parameters are not identified and the incidental parameter λ may be on the boundary of its $[0, 1]$ parameter space.[9]

Fortunately, interest in genetic mapping has led to recent progress in determining the asymptotic distribution of the LRTS in tests for homogeneity in binomial mixture models.[10] Geneticists study whether two loci are genetically linked (located close together on a chromosome) by studying recombinations between the corresponding traits (say, traits A and B) in families, with the families assumed to be independent of each other. With a homogenous population and each trait caused by a single loci the recombination probability, θ, is $\frac{1}{2}$ if the loci are not linked and less than $\frac{1}{2}$ if they are linked. This case can be modelled using a single binomial recombination probability. However, in some cases trait A may be caused by either of two different loci, only one of which is linked to trait B. In this case, loci will appear to be linked in some families but not in others. This can be modelled by a binomial mixture model in which one component has binomial recombination probability less than $\frac{1}{2}$ and the other has probability $\frac{1}{2}$. The mixing parameter λ represents the proportion of families in which the loci are linked. A further possibility is that trait A is caused by either of two loci, both linked to the B loci but with one more closely linked than the other so that each loci gives a different recombination probability. This can be modelled using a binomial mixture model with two components both with binomial recombination probabilities less than $\frac{1}{2}$. In my analysis, players replace individuals, independent repetitions of the game replace families and a player's choice of action replaces whether parental traits are recombined in the individual. The number of players can vary across repetitions in the same way that the number of individuals can vary across families.

Following Lemdani and Pons (1997, Theorem 3) and Chen and Chen (2001, Theorem and Example 2), the asymptotic distribution of the LRTS under the null hypothesis of a single binomial distribution with binomial probability θ_0, when the alternative hypothesis allows a

[9]In a general formulation of a two component mixture with pdf of y $\lambda f(y, \theta_1) + (1 - \lambda) f(y, \theta_2)$ and under the assumption that $\lambda > \frac{1}{2}$, the null of a single distribution with parameter θ_1 is consistent with either $\lambda = 1$, in which case θ_2 is not identified and λ is on the boundary of its parameter space, or $\theta_1 = \theta_2$ in which case λ is not identified.

[10]For example Chernoff and Lander (1995), Liang and Rathouz (1995) and Lemdani and Pons (1995, 1996, 1997). Ott (1999), Section 10, provides a explanation of different tests for genetic linkage.

mixture with two binomial components, is the distribution of

$$\sup_{\theta \in \Theta} (W(\theta))^2 I(W(\theta) \geq 0) \tag{2.28}$$

where $I(W(\theta) \geq 0)$ is an indicator which takes value 1 (0 otherwise) if $W(\theta) \geq 0$. $W(\theta)$ is a centered Gaussian process with mean zero and covariance defined by

$$\frac{\Sigma_{11}\Sigma_{22}(\theta, \theta')}{(\Sigma_{11}\Sigma_{22}(\theta, \theta))^{\frac{1}{2}}(\Sigma_{11}\Sigma_{22}(\theta', \theta'))^{\frac{1}{2}}} \tag{2.29}$$

where

$$\Sigma_{11} = \frac{\sum_j j\mu_j}{\theta_0(1-\theta_0)} \tag{2.30}$$

$$\Sigma_{22}(\theta, \theta') = \sum_j \frac{\mu_j}{(\theta-\theta_0)^2(\theta'-\theta_0)^2} \left\{ \left[1 + \frac{(\theta-\theta_0)(\theta'-\theta_0)}{\theta_0(1-\theta_0)} \right]^j - 1 - j\frac{(\theta-\theta_0)(\theta'-\theta_0)}{\theta_0(1-\theta_0)} \right\} \tag{2.31}$$

and μ_j is the proportion of observations with j members (in my setting, repetitions with j players). Θ is the parameter space over which it is assumed that the binomial probabilities can range. In the general case where the binomial probabilities can take any value between 0 and 1, $\Theta \in [0, 1]$; in testing for genetic linkage the probabilities are typically restricted to be less than $\frac{1}{2}$ so $\Theta \in [0, \frac{1}{2}]$.

Calculating the exact distribution of the supremum of the square of a Gaussian process is not straightforward although simulations can be used. However, Chen and Chen (2001) argue, based on Beran (1988), that because the limiting distribution of the LRTS under the null exists and is a continuous function of θ_0, a parametric bootstrap procedure can be used. Therefore I use the following testing procedure:

1. use the actual data to estimate $\widehat{p^*}$, the single binomial equilibrium choice probability, and the value of the log-likelihood ($\ln L_{null}$) under the null hypothesis that there is only one equilibrium;

2. use the actual data to estimate $\widehat{\beta}, \widehat{\alpha}, \widehat{\lambda}$ and the value of the log-likelihood under the alternative hypothesis that there may be two equilibria. Use the log-likelihoods from

steps 1 and 2 to calculate the LRTS for the actual data ($\text{LRTS}_{actual} = -2(\ln L_{null} - \ln L_{alternative})$);

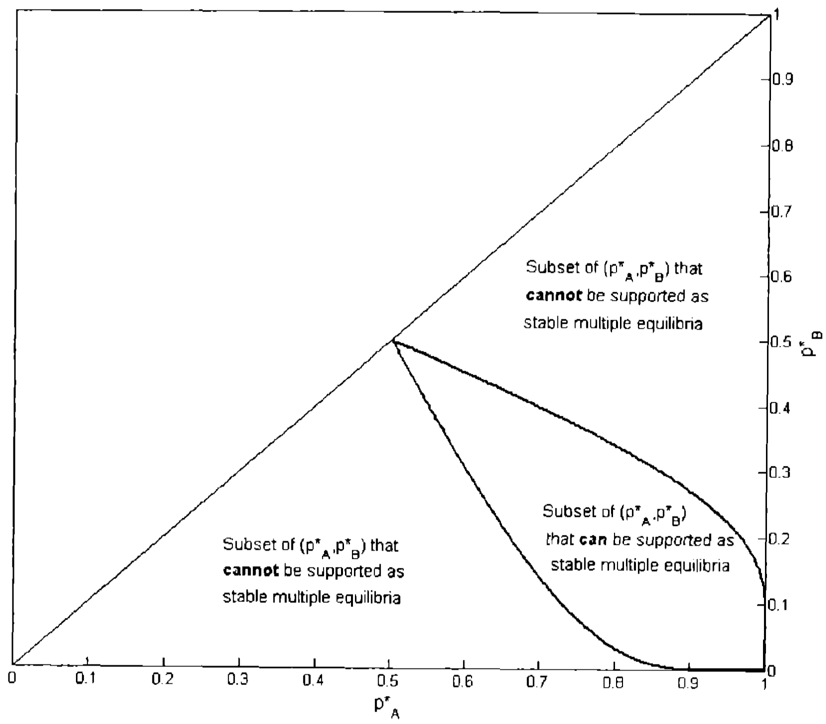
3. use $\widehat{p^*}$ as the binomial choice probability to create a new set of data, under the assumption that there is only one equilibrium, with the same number of repetitions as in the actual data and the same number of players in each repetition. Repeat steps 1 and 2 (see discussion below for how step 2 is repeated for the bootstraps) and calculate LRTS_{bs};

4. repeat step 3 BS times (BS is set to be 499). The jth-order statistic from the LRTS bootstrap replications estimates the $\frac{j}{(BS+1)}th$ quantile of the distribution of the LRTS under the null (for example, ordering the LRTS_{bs} from the smallest to the largest with $BS = 499$, the $475th$ LRTS estimates the 0.95 quantile).

The functional form assumptions in the model, particularly of Type I extreme value errors, restrict the set of pairs of binomial mixture probabilities (Θ) which can be supported as stable multiple equilibria. This is illustrated in Figure 2-4. In particular, pairs which involve coordination on the same action (e.g., $p_A^*, p_B^* > 0.5$) and pairs in which one equilibrium involves a high degree of coordination and the other a low degree of coordination (e.g., $p_A^* = 0.95, p_B^* = 0.45$) cannot be supported. While these restrictions are sensible (if coordination is sufficiently important to support a highly coordinated equilibrium it cannot also be sufficiently unimportant to support a very uncoordinated equilibrium), the exact location of the boundaries in Figure 2-4 are determined by the distributional assumption.

When estimating the model using the actual data under the alternative hypothesis that there may be more than one equilibrium, I always impose these functional form restrictions. However, when computing the bootstrap values of the LRTS under the alternative I do not impose the restrictions, allowing any pair of binomial probabilities whether they can be supported as stable equilibria or not. This is because, as I explain in the Appendix, it is much quicker to estimate binomial probabilities and λ using an EM algorithm when the probabilities are unrestricted than when they are restricted and the restrictions are binding (which they frequently are with bootstrap replications generated under the null). This means that in calculating the LRTS for the bootstraps I maximize the likelihood, under the alternative, over a strictly larger set of possible choice probabilities than I use for the actual data. Under the null, I maximize over

Figure 2-4: p_A^*, p_B^* Pairs, with $p_A^* > p_B^*$, Supported as Distinct Multiple Equilibria with ε IID Type I Extreme Value



the same set of choice probabilities for the bootstrap and actual data. This produces a more conservative assessment of the significance of the multiple equilibria than if the restrictions were imposed in calculating the LRTS for the bootstrap replications.

2.5 Estimation

I use an EM algorithm to find Maximum Likelihood estimates (MLE) of the parameters. This algorithm is widely used to estimate mixture models (McLachlan and Krishnan (1997), McLachlan and Peel (2000)) and it clarifies the link between the complete data problem I would face if I observed the identity of the equilibrium in each repetition (Z_m^A) and the incomplete data problem I actually face. This section briefly outlines the approach with full details provided in the Appendix.

2.5.1 Estimation with One Equilibrium

To test for multiple equilibria I need to estimate the model under the null hypothesis of a single equilibrium in which players in all of the observed repetitions of the game choose action 1 with the same probability p^*. The likelihood for the sample is

$$L = \prod_{m=1}^{M} \frac{(n_{m1}+n_{m2})!}{n_{m1}!n_{m2}!} p^*(\beta,\alpha)^{n_{m1}}(1-p^*(\beta,\alpha))^{n_{m2}} \tag{2.32}$$

where M is the number of observed repetitions. As explained in Section 2.3 β and α are not separately identified but if α is assumed to be zero then, as $p^* = \frac{e^\beta}{1+e^\beta}$, the MLE of β is simply

$$\widehat{\beta} = \ln\left(\frac{\sum_{m=1}^{M} n_{m1}}{\sum_{m=1}^{M} n_{m2}}\right) \tag{2.33}$$

2.5.2 Estimation with Multiple Equilibria

The equilibrium choice probabilities are $p_A^*(\beta,\alpha)$ and $p_B^*(\beta,\alpha)$ with $p_A^*(\beta,\alpha) \geq p_B^*(\beta,\alpha)$.[11] The incomplete data likelihood is

$$L = \prod_{m=1}^{M} \frac{(n_{m1}+n_{m2})!}{n_{m1}!n_{m2}!} \left(\begin{array}{c} \lambda p_A^*(\beta,\alpha)^{n_{m1}}(1-p_A^*(\beta,\alpha))^{n_{m2}} \\ +(1-\lambda)p_B^*(\beta,\alpha)^{n_{m1}}(1-p_B^*(\beta,\alpha))^{n_{m2}} \end{array} \right) \tag{2.34}$$

The complete data log-likelihood (Z_m^As observed) would be

$$\ln L_c = \sum_{m=1}^{M} \ln\left(\frac{(n_{m1}+n_{m2})!}{n_{m1}!n_{m2}!}\right) + \left(\begin{array}{c} Z_m^A \left[\ln\lambda + n_{m1}\ln p_A^*(\beta,\alpha) + n_{m2}\ln(1-p_A^*(\beta,\alpha))\right] + \\ (1-Z_m^A)\left[\ln(1-\lambda) + n_{m1}\ln p_B^*(\beta,\alpha) + n_{m2}\ln(1-p_B^*(\beta,\alpha))\right] \end{array} \right) \tag{2.35}$$

The EM algorithm exploits the fact that the parameter values which maximize (2.34) are also solutions to iterating a two-step Expectation(E)-Maximization(M) procedure (Dempster et al. (1977)). The E-step takes the conditional expectation of (2.35) by replacing each Z_m^A indicator

[11] Redner (1981) shows that when the data is generated from a true mixture of distributions the standard conditions for consistency of MLE are satisfied. Feng and McCulloch (1996) show that MLE of mixtures converge to the non-identifiable subset of the parameter space containing the true parameters when the data is generated by a single distribution rather than a true mixture. See also the discussion in McLachlan and Peel (2000) p. 43.

with its expected value, τ_m. τ_m is the conditional (or "posterior") probability that observation m is from equilibrium A given the data and the current iterated value of the parameters. The M-step maximizes the conditional expectation of (2.35) with respect to the parameters β, α and λ to produce new parameter estimates which are used in the next E-step. The Appendix outlines two alternative procedures for the M-step and describes when each is used. The E- and M- steps are iterated until convergence to give the final parameter estimates and these estimates are then substituted back into (2.34) to give the maximized value of the incomplete data likelihood.[12] The final estimates of the τs can be used to classify repetitions into different equilibria: if all misclassifications are equally costly and correct classifications are costless, the Bayes Rule will classify each repetition to the equilibrium which has the highest posterior probability (McLachlan and Peel (2000), p. 29). Standard errors are calculated using a bootstrap.

2.6 The Timing of Commercial Breaks by Music Radio Stations

I estimate the basic model of Section 2.2 and some extensions using a new dataset on the timing of commercial breaks by contemporary music radio stations. As explained in the Introduction, these stations tend to play commercials at similar times but it is unclear whether this is due to an incentive to coordinate or other factors, such as the way in which station ratings are estimated, which could also lead stations to make similar choices. My approach here is to use the possibility that stations in different local radio markets coordinate on playing commercials at slightly different times to identify the incentive to coordinate.

I now describe how I interpret the three components of a player's payoff function (2.1) in terms of the factors which affect a station's timing of a commercial break. I treat time as being divided into discrete intervals in which a station either plays music or has a commercial break. The β_ts reflect how attractive interval t is, on average, for a commercial break independent of other stations' timing choices. For example, Arbitron's method for estimating station ratings would make the β_ts low for intervals containing the quarter-hour points The β_ts are assumed to be the same across stations and across markets. One justification for this is that Arbitron's

[12]It is well-known that likelihoods in mixture models may have multiple local maxima (McLachlan and Peel (2000), chp. 2). In practice this appeared not to be a problem in my application when estimating this model.

methodology is the same in all markets.[13] The αP_{-it} term allows a station's payoff from having a commercial at time t to depend on the proportion of other stations simultaneously having commercials. This formulation can be justified by a simple model of listener preferences and behavior if it is assumed that a station's profits increase linearly in the number of people listening to its commercials.[14] Suppose that there are N symmetric stations and N units of listeners. Every listener has a first choice station and a second choice station, and these preferences are independent so that the second choices of listeners with the same first choice station are split equally between the other stations. Proportion $1-s$ of listeners are "non-switchers" who always listen to their first choice station irrespective of what it plays. Proportion s of listeners are "switchers" who listen to their first choice unless it has commercials and their second choice does not, in which case they listen to their second choice. In this case, station i's audience at any point during a commercial break is $1-s+s\frac{N_{-i}}{N-1}$ where N_{-i} is the number of other stations simultaneously playing commercials. The final component of the payoff is an IID error term which gives each station idiosyncratic preferences over the different intervals. These errors reflect two aspects of the timing decision. First, even though a commercial break may be scheduled to start at a particular time (the "clock strategy" for the break), the actual start time will vary to create the best possible "sound" for the station. For example, songs differ in length and few stations would want to break off in the middle of a song to play a commercial.[15] In addition, phone-ins or DJ chat may overrun their scheduled times if listeners are likely to be enjoying them. Second, a program director may have idiosyncratic preferences over the timing of commercials which he may consider to be more important than trying to coordinate with other stations given that their timing of commercials will also vary. For example, a station has to announce its call sign and city of license at the top of the hour. Some program directors may believe that this announcement should be preceded by a song while others may consider

[13] One can think of explanations which would invalidate this assumption: for example, the afternoon rush hour may last longer in some markets and this may affect station timing patterns. Discussions with people in the industry indicated that this was not likely to affect the kind of 5 minute timing decisions which I examine here. If one had data on traffic patterns then β could be parameterised to control for this possibility.

[14] One possible objection to this assumption is that advertisers do not know the audience of the commercials because radio ratings do not differentiate between the audience of the commercials and other kinds of programming. However, Dick and McDowell (2003) show how the standard ratings numbers to which advertisers do have access can be used to estimate the relative amount of commercial avoidance on different stations.

[15] Warren (2001), p. 24 explains that sweeping the quarter-hours with music "can be done some of the time. But it can't be done consistently by very many stations. Few songs are 2:30 minutes long any more".

this to be a natural time for a commercial break. A program director may also try to develop a reputation for having, for example, "weather and travel on the 3s", which necessitates a certain arrangement of other programming, including commercials, and may preclude coordination.

The basic model involves players choosing between two different actions. I examine the timing decision of stations which have one commercial break during the last part of the hour (the part with the most commercials, see Figure 2-1) and estimate the model using data on which of two discrete five minute time intervals contains the median minute of the break. Multiple equilibria in the timing game should result in disproportionately many stations in each market choosing the same interval relative to average choices across markets. In taking this approach, I abstract from the decision of stations to have a commercial break in the last part of the hour. In estimating the basic model I also make the additional simplifying assumption that the expected proportion of stations having a break in either of the two intervals is the same across markets, days and equilibria in a particular hour. This allows me to treat the game as being played between only those stations which have commercials in either of the time intervals and makes equilibrium strategies independent of the number of stations with commercials.[16] This simplifies estimation which is an important consideration given that I test for multiple equilibria using a bootstrap. Section 2.6.5 provides estimates from a model which takes some account of the fact that some stations very rarely have commercials in either of the intervals.

The rest of this section is organized in the following way. Section 2.6.1 details the data. Section 2.6.2 provides the results from estimating the basic model with each market-day treated as an independent observation of the game. Section 2.6.3 presents estimates which use the time series aspect of my data on station timing choices to distinguish between the scheduled (clock strategy) times for commercial breaks and actual timing. Section 2.6.4 presents estimates when I allow market characteristics to affect the incentive to coordinate and equilibrium selection. Section 2.6.5 extends the model of Section 2.6.3 to allow a richer examination of timing strategies including those of stations which do not typically have commercials in either of the two intervals

[16] If this common expected proportion of stations is γ, and stations' payoffs are affected by the total proportion of stations playing commercials in interval t rather than the proportion of stations having commercials in either of the intervals which choose interval t, then the only change to the estimates I present is that α should be mulitiplied by $\frac{1}{\gamma}$. γ can be easily estimated as simply the proportion of stations having commercials in either of the intervals (see Table 3). Of course, if there are some markets in which disproportionately many stations avoid playing their commercials at the end of the hour this may provide further evidence of multiple equilibria and coordination on the timing of commercial breaks.

of interest.

2.6.1 Data

I create a new dataset using daily airplay logs collected by Mediabase 24/7, which uses electronic voice recognition technology to collect data on music airplay. I have daily airplay logs from the first five weekdays of each month from 2001 for 1,063 contemporary music radio stations tracked by Mediabase during that year, a maximum of 60 days per station. Listener switching to avoid commercials is a particular problem for contemporary music stations because there may be many quite similar stations in a market which are close substitutes for listeners, they have more young listeners who are more likely to switch stations to avoid commercials and they play sequences of distinct songs which do not provide a natural reason for listeners to want to hear what follows immediately after a commercial break.[17] BIAfn's *Media Access Pro* database classifies these 1,063 stations as being home to 146 different Arbitron-defined local radio metro-markets and 1,061 of them as coming from 7 music format categories: Adult Contemporary, Album Oriented Rock/Classic Rock, Contemporary Hit Radio/Top 40, Country, Oldies, Rock and Urban.[18] I do not have data on stations from other music categories, such as Classical, or non-music categories. Table 2.1 presents some information on the proportions of rated contemporary music stations and rated listening in these markets which are covered by sample: while many contemporary music stations are not in the sample, the sample does account for a large majority of contemporary music radio listening especially in larger markets.[19] Although

[17]Median listener ages for Country, Adult Contemporary, Urban, Rock and CHR stations are 44, 41, 29, 26 and 25 compared with 58 and 56 for Classical and News/Talk stations (Katz Media Research website www.krgspec.com). McDowell and Dick (2003) find that younger radio listeners are more likely to switch stations to avoid commercials.

[18]Each station has one home market which is based on its city of licence or the market where it has most of its listeners. I treat WMUS-FM as home to Grand Rapids, MI even though BIAfn lists it as home to Muskegon, MI. WMUS-FM is the only station in my data which is home to Muskegon and based on its Fall 2001 cume rating (the number of listeners ever listening to the station) it has more listeners in Grand Rapids than in Muskegon. The two stations not included in the 7 categories are KDIS-AM (Miscellaneous) and KHPT-FM (Variety). Their logs show that they play a lot of contemporary music and I include them in the estimation.

[19]To understand how to read the Table look at the Country entry for Arbitron metro-markets 1-70. I have airplay data on at least one Country station which is home to the market in 62 of the 70 markets. In these 62 markets there are 139 rated Country stations and I have airplay data on 93 of these, and these 93 account for 91.9% of listening to home market Country stations in these 62 markets. "All contemporary music" groups together the seven categories listed. Rated stations are those with positive listening shares in Arbitron reports. I have no data from Puerto Rico (market rank 13). There are 1,061 airplay stations in the table because BIAfn counts 2 of the airplay stations in other categories.

Table 2.1: Coverage of Airplay Sample Stations by Format Category

Format Category	Number of Airplay Metro-Markets	Number of Home to Market Rated Stations	Number of Home to Market Rated Airplay Stations	Average % of Fall 2001 Home Listening covered by Airplay Sample
Arbitron Metro-Markets Ranked 1-70 (1 is New York and 70 is Ft. Myers, FL)				
All contemporary music	69	1004	700	83.3
Adult Contemporary	66	221	154	84.3
AOR/Classic Rock	65	111	96	94.4
CHR/Top 40	64	131	110	94.6
Country	62	139	93	91.9
Oldies	44	64	44	92.1
Rock	60	145	119	93.2
Urban	43	132	84	83.0
Arbitron Metro-Markets Ranked 71 and above (71 is Knoxville, TN)				
All contemporary music	77	753	361	67.1
Adult Contemporary	54	127	76	79.9
AOR/Classic Rock	33	63	44	83.3
CHR/Top 40	58	95	72	89.6
Country	57	132	73	85.7
Oldies	1	3	1	40.7
Rock	40	76	57	86.7
Urban	26	57	38	85.9

Table 2.1 is broken down by music category, I treat stations in all categories symmetrically in estimation. This treatment is justified because many listeners switch stations across these quite similar music categories to avoid commercials.[20]

Table 2.2 shows one hour of a Classic Hits (Rock) station daily log. The log is a list of songs (with artist and release years) with the start time of each song and indicators for whether a commercial break aired between the songs. There is no information on which particular commercials are played. I process each hourly log in the following way to generate the interval data used in estimation:

1. create a minute-by-minute schedule (5:00, 5:01, 5:02 etc.) and mark the start of each song;

[20]Estimation of the model separately by category would also be difficult because of Condition 4 in Section 2.3: identification depends on having observations with at least 3 stations and there are relatively few market-category combinations with three stations having commercials in the last part of each hour.

Table 2.2: Extract from a 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

2. calculate the median length of each song using those log entries (for all station logs from all hours) where a song is followed by another song with no commercial break;

3. fill out the schedule with songs assuming that each song is played its median length (if step 2 does not provide a length assume that it is 4 minutes, the median length of all of the songs);

4. fill out commercial breaks into the gap between songs if a commercial break is indicated;

5. identify the median minute of each commercial break; and

6. allocate each commercial break to a 5 minute time interval based on the median minute of the break. The time intervals are :03-:07, :08-:12, ..., :58-:02, so that the quarter-hour points, which have relatively few commercials, are in the middle of intervals rather than on the boundaries between them. This procedure allocates each commercial break, which may last several minutes, to exactly one time interval.

There may be measurement error in the allocation of breaks to intervals. In particular, the logs do not identify periods of DJ chat, news or travel information which may be placed immediately before or after a break so I may wrongly identify the median minute of a commercial break and allocate it to the wrong interval. To reduce this problem I drop station-hours with less than 7 songs because these have a large amount of time unaccounted for in the log. However, any remaining errors, as long as they are independent across stations within a market, should make it harder rather than easier to find evidence of multiple equilibria (commercial breaks clustered at different times in different markets) and would also lead me to underestimate the incentive to coordinate.[21]

I focus on two time intervals, :48-:52 (interval 1) and :53-:57 (interval 2). These intervals have the most commercials (Figure 2-1) and neither includes a quarter-hour point so that it is plausible that they have similar β_ts and we could observe multiple equilibria with some markets coordinating on interval 1 and others coordinating on interval 2. Table 2.3 shows the proportion of station-hours (with a commercial break at some point during the hour) which have breaks in each of these intervals and in both intervals for the eight hours I use in estimation. The model assumes that stations make a single discrete choice so I drop the very small proportion of observations with breaks in both intervals. I also note that the minutes on the boundary

Table 2.3: Proportion of Stations with Commercial Breaks in the 2 Intervals for 8 Different Hours

	Number of station-hours	Proportion Interval 1 only :48-:52	Proportion Interval 2 only :53-:57	Proportion Both Interval 1 & Interval 2
3-4am	39,317	0.248	0.198	0.002
12-1pm	48,889	0.311	0.281	0.002
3-4pm	49,716	0.332	0.267	0.001
4-5pm	49,331	0.317	0.290	0.002
5-6pm	48,567	0.326	0.306	0.001
6-7pm	49,015	0.336	0.258	0.001
9-10pm	46,329	0.283	0.304	0.001
10-11pm	45,074	0.284	0.291	0.001

of the two intervals (:52 and :53) have the most commercials in each hour (Figure 2-1). If there are markets in which stations coordinate on playing commercials in these minutes they are likely to appear in my data as quite uncoordinated (commercials spread evenly across the intervals). This should also make it harder to find evidence of multiple equilibria and would

[21]This kind of misallocation creates measurement error in the discrete dependent variable, a problem discussed in some detail by Hausman et al. (1998).

lead me to underestimate the incentive to coordinate.

I estimate the model separately for the eight hours listed in Table 2.3. Four of them are drivetime hours and the other four are non-drivetime hours. The incentive to coordinate should be stronger during drivetime, because more listeners are in their cars and it is easier for in-car listeners to switch stations. 3-7pm is defined by Arbitron as the "afternoon drive" daypart.[22] The four non-drivetime hours should have different listening patterns (for example, proportion of listeners at work) except that all should have a lower proportion of in-car listeners than the drivetime hours.

I have a maximum of 60 days of data for each station for each hour. However, the panel is unbalanced (not every station has data for every day). The airplay sample grows during the year especially in smaller markets and a few stations exit the sample. There are also a large number of station-days missing from the Mediabase database and in some hours stations may have non-music programming and the log just lists the name of the program. As noted above I also drop hours with less than 7 songs. This leaves a mean (median) number of stations per hour per day of 833 (900) for the 4 drivetime hours and 813 (872) for 4 non-drivetime hours. The mean (median) number of stations per hour per day with some commercials during the hour is 819 (883) for drivetime hours and 748 (805) for non-drivetime hours.

2.6.2 Results from the Basic Model: Each Market-Day is an Independent Repetition of the Game

Table 2.4 presents the results from estimating the model of Section 2 separately for each hour. Each market-day observation is treated as a separate and independent observation of the game. The first box-row in the table gives the estimation results when it is assumed that there is only one equilibrium so that β and α are not separately identified. The reported estimate of β assumes that $\alpha = 0$ (no incentive to coordinate). I also present the implied probability that a

[22] I use the afternoon drive rather than the morning drive because many of the stations in the sample have such a large amount of non-music programming (news, weather, travel, DJ chat) during the morning drive that commercial breaks cannot be allocated to time intervals accurately. This type of programming may also result in more interaction in the timing of commercials with non-music stations. Some stations also have pure talk programming, such as "The Howard Stern Show" in the morning and for these station-hours the hourly logs are blank except for the name of the show. In contrast, the vast majority of stations play music with a few breaks for commercials during the afternoon drive.

station with a break in either of the two intervals chooses interval 1 (:48-:52) and it is close to $\frac{1}{2}$ in all hours. The second box-row presents the results when I allow for two equilibria so that β and α are separately identified if there are multiple equilibria in the data. For every drivetime hour the model with two equilibria fits better than a model with one equilibrium and β and α can be estimated. I will consider the degree of coordination implied by these estimates in a moment. On the other hand, for three of the non-drivetime hours the estimated parameters are within the region of the parameter space where β and α cannot be separately identified, i.e., the model with only one equilibrium fits just as well as the model which allows for two equilibria.[23] This does not imply that there is no incentive to coordinate during these hours - there should be because some listeners switch stations to avoid commercials outside drivetime - but it does mean that the incentive cannot be separately identified from other factors which may make one of the intervals more attractive for commercials. For these hours I present coefficient estimates which assume that $\beta = 0$. This choice is entirely arbitrary and I do not present standard errors on these estimates.

The third box-row presents the results from the test for multiple equilibria. I list the LRTS estimated using the actual data and the 90^{th}, 95^{th} and 99^{th} percentiles of the bootstrapped LRTS distribution. For each hour 3-6pm the test statistic is clearly significant (based on the bootstraps) at the 1% level and for 6-7pm it is significant at the 2% level. This provides reasonably strong evidence for multiple equilibria during drivetime, especially as the test is conservative (as described in Section 2.4). For the three non-drivetime hours in which the one equilibrium model fits as well as the model which can have two equilibria the LRTS is zero: the LRTS is also zero in about one half of the bootstrap replications. For the remaining non-drivetime hour (9-10pm) the LRTS is very close to zero and completely insignificant even though the estimated λ is close to $\frac{1}{2}$.

Comparison between Nash Equilibrium and Joint Payoff Maximizing Strategies Table 2.4 also presents the implied equilibrium probabilities of choosing interval 1 in each of the Bayesian Nash equilibria for the hours in which the two equilibria model fits better than

[23]This is consistent with Feng and McCulloch's (1996) result that the MLE should converge to the non-identified subset of the parameter space containing the true parameters if the data is generated from a single distribution rather than a true mixture.

the single equilibrium model. For example, the 4-5pm equilibrium A involves stations choosing interval 1 with probability 0.591 (interval 2 chosen with probability 0.409) and equilibrium B has interval 1 chosen with probability 0.456 (interval 2 chosen with probability 0.544). The degree of coordination is not particularly high in any of the drivetime hours i.e., quite a high proportion of stations do not choose the interval on which the stations appear to be trying to coordinate.

An important feature of this game is that the Nash equilibrium degree of coordination may be sub-optimal (Section 2.2.1). In the context of the timing of commercials, this is because each station considers the effect of its timing decision on its own audience and its own costs of scheduling (its εs) but not the effect on the audience of the commercials on other stations, i.e., there is an externality. I therefore also present, for the 4 drivetime hours which have significant evidence of multiple equilibria, the implied expected joint payoff maximizing probability of choosing interval 1 (Section 2.2.1 explains the calculation): these probabilities imply almost perfect coordination with each station choosing the interval with the higher average payoff (interval 1 for 3-5pm and 6-7pm) with probability 0.98.[24] This is interesting for two reasons: first, it shows that the externality has a large effect on timing choices (and therefore on the number of people listening to commercials) and second, it shows that the results are not inconsistent with the intuition that the total number of listeners to commercials would be maximized by all of the stations in a market having their commercial breaks at the same time.

Testing for Multiple Equilibria Separately in Large Markets and Small Markets Table 2.5 provides the results of testing for multiple equilibria separately in the largest 28 metro-markets in the sample (Arbitron ranks 1 (New York City) - 29 (Kansas City), I have no data on 13 (Puerto Rico)) and in all of the smaller markets (ranks 30 (San Jose) and lower). This division groups markets with more than $1\frac{1}{2}$ million people aged 12 and above into the large market group. There are many more markets in the small market group but there are more

[24]As there is some common ownership of music stations in most markets it might seem inappropriate to assume that none of the externality is taken into account in Nash equilibrium. I therefore also calculated expected joint payoff maximizing strategies under the alternative assumption that one half of the externality is internalized in equilibrium, so that the estimates of α in Table 4 are treated as estimates of $\frac{3}{2}\alpha$ (the average HHI for home to market contemporary music stations is 0.28 so that it seems unlikely that more than one half of the externality is internalized). Under this assumption expected joint payoff maximizing strategies would still be much more coordinated than Nash equilibrium with the coordinated interval being chosen with probability 0.892.

stations, on average, in each of the large markets which makes it potentially easier to identify multiple equilibria in the large markets. There is consistently strong evidence for multiple equilibria in the smaller markets during drivetime, but no evidence for multiple equilibria in these markets outside drivetime. In the large markets there is only any evidence of multiple equilibria in one non-drivetime hour (9-10pm) for which the LRTS is significant at the 10% level: this appears likely to be a statistical anomaly. I investigate the possibility that there is less coordination in large markets further in Section 2.6.4 by explicitly allowing the incentive to coordinate to depend on market size.

2.6.3 Model 2: Stations Choose Clock Strategies Implemented with Noise

There are two concerns with treating each market-day observation as an independent repetition of the game. First, if stations tend to choose the same time for commercials every day then treating each market-day observation as independent risks overstating the significance of multiple equilibria. A station manager explained to me that scheduled (clock strategy) times for breaks tend to remain the same from day-to-day so that programming such as weather and travel updates or competitions, which tend to attract listeners, can air at predictable times. Second, if the actual time at which a commercial is played reflects the station's clock strategy plus some almost unavoidable noise, because of the difficulty in placing breaks around songs of different length, it is appropriate to distinguish between coordination in the choice of clock strategies and actual timing. As I have panel data I can use the daily timing data to infer stations' clock strategies, assuming that these clock strategies remain the same from day-to-day.

Model

Suppose a station's program director makes a clock strategy decision over which interval to play the commercial break in at the start of each week w, and that β and ε affect preferences over clock strategies. ε no longer reflects day-to-day scheduling problems but instead captures idiosyncratic preferences including wanting "weather and travel on the 3s" or music just before announcements at the top of the hour. The clock strategy is implemented with probability q and the other interval is chosen with probability $(1-q)$. This captures real time scheduling problems and it is assumed to be common across stations and not to be a probability which stations can choose.[25] I assume that q does not vary between equilibria or clock strategies, an assumption which I relax in Section 2.6.5. As before, the payoff from coordination comes from the degree of coordination in actual timing. If other stations in i's market choose interval 1 for their clock strategy in week w with probability p_{-iw}, the expected proportion of them choosing interval 1 for the actual timing of their commercial is simply

$$p_{-iw}q + (1 - p_{-iw})(1 - q) \tag{2.36}$$

and in equilibrium the probability, p_w^*, of choosing interval 1 for the clock strategy will satisfy

$$p_w^* = \frac{e^{\beta+\alpha(p_w^* q+(1-p_w^*)(1-q))}}{e^{\beta+\alpha(p_w^* q+(1-p_w^*)(1-q))} + e^{\alpha(p_w^*(1-q)+(1-p_w^*)q)}} \tag{2.37}$$

The model has at most two stable equilibria. An observation now consists of the realized times of commercials during the week for every station in the market which has at least one commercial during one of the two time intervals during the week. There is an additional incomplete data aspect to the problem in that each station's choice of clock strategy is not observed. If there is a single equilibrium and a market has N stations with station i choosing interval 1 on n_{i1} days and interval 2 on n_{i2} days, the incomplete data probability of the observation is

$$\Pr\left(\begin{array}{c} n_{11}, n_{12} \\ \ldots \\ n_{N1}, n_{N2} \end{array} |\beta, \alpha\right) = \prod_{i=1}^{N} \frac{(n_{i1} + n_{i2})!}{n_{i1}! n_{i2}!} \left(\begin{array}{c} p^*(\beta, \alpha, q) q^{n_{i1}} (1 - q)^{n_{i2}} + \\ (1 - p^*(\beta, \alpha, q))(1 - q)^{n_{i1}} q^{n_{i2}} \end{array}\right) \tag{2.38}$$

[25] Of course, one could write down a model in which q could be chosen at least to some extent by the stations or could be a function of the degree of coordination in clock strategies. Here I am assuming that q is in practice very hard to control. This treatment would also be appropriate if q captures measurement error in the process of allocating breaks to intervals. Consistent with the assumption that q cannot be controlled by stations, I find that q is almost identical across hours even though the incentive to coordinate should differ across hours.

With two equilibria and the same A, B and λ notation as before the incomplete data probability of an observation is

$$\Pr\left(\begin{array}{c} n_{11}, n_{12} \\ \ldots \\ n_{N1}, n_{N2} \end{array} |\beta, \alpha, \lambda\right) = \lambda \prod_{i=1}^{N} \frac{(n_{i1}+n_{i2})!}{n_{i1}!n_{i2}!} \left(\begin{array}{c} p_A^*(\beta, \alpha, q) q^{n_{i1}} (1-q)^{n_{i2}} + \\ (1-p_A^*(\beta, \alpha, q))(1-q)^{n_{i1}} q^{n_{i2}} \end{array}\right) \tag{2.39}$$

$$+ (1-\lambda) \prod_{i=1}^{N} \frac{(n_{i1}+n_{i2})!}{n_{i1}!n_{i2}!} \left(\begin{array}{c} p_B^*(\beta, \alpha, q) q^{n_{i1}} (1-q)^{n_{i2}} + \\ (1-p_B^*(\beta, \alpha, q))(1-q)^{n_{i1}} q^{n_{i2}} \end{array}\right)$$

In either case q is identified from how consistently individual stations make the same timing choice. If all stations did exactly the same thing every day the estimated value of q would be 1. It is natural to impose that $q > \frac{1}{2}$ so that the clock strategy interval is chosen with higher probability than the other interval. As described in the Appendix this model is also estimated using an EM algorithm and, as before, I use a bootstrap for the LRTS to test for multiple equilibria.

I estimate this model under two different assumptions about how frequently stations take clock strategy decisions. The first assumption is that each station takes a new and independent clock strategy decision each week (as I have one week of data each month this is equivalent to assuming that a new decision is taken every calendar month). The second assumption is that each station takes only one clock strategy decision for the entire year. As I test for multiple equilibria in clock strategies, this assumption minimizes the possibility that using multiple observations on each station will lead me to overstate the significance of multiple equilibria.

Results of the Clock Strategy Model

Tables 2.6 and 2.7, organized in the same way as Table 2.4, present the results assuming that clock strategy decisions are taken weekly and annually respectively. If I assume that stations take clock strategy decision weekly, the likelihood ratio test statistics are more significant during drivetime than in the basic model (Table 2.4). If I assume that decisions are taken annually then the test statistics are of similar significance to the basic model and are significant at the 1% level in all hours. The effective reduction in the number of observations from looking at clock strategies is offset for two reasons: there is more coordination in the choice of clock strategies than in actual timing and a station's clock strategy can be identified more accurately with more time series observations. In both cases there is little evidence of multiple equilibria outside drivetime.[26] The estimated value of q is lower for each hour with annual clock strategy decisions than with weekly decisions which suggests that some stations do change their clock strategies during the year.

Comparison between Nash Equilibrium and Joint Payoff Maximizing Strategies Tables 2.6 and 2.7 also show the implied Nash equilibrium probabilities of stations choosing interval 1 for their clock strategy. There is more coordination in the choice of clock strategies than in actual timing (compare Table 2.4). However coordination is still far from perfect with around $\frac{1}{3}$ of stations choosing the non-coordinated interval for their clock strategy in each equilibrium. This suggests that program directors' idiosyncratic preferences over timing arrangements are important and can be more important to them than trying to coordinate on timing given that coordination is necessarily imperfect.

I also report the implied expected joint payoff maximizing probabilities of choosing interval 1 for the clock strategy. This calculation assumes that stations cannot increase q by, for example, more carefully selecting the songs that they play. As in the basic model, the estimates imply that joint payoff maximization would result in almost perfect coordination in clock strategies. If q could be increased, the implied joint payoff maximizing choice of clock strategies would be even more coordinated.

Market Classification and Equilibrium Selection in Geographically Close Markets As mentioned in Section 2.5.2, the estimates can be used to classify markets into different equilibria. Assuming that all misclassifications are equally costly and correct classifications are costless, the Bayes Rule for classification is that a market should be classified into a particular equilibrium if and only if the posterior probability of the market being in that equilibrium is higher than the posterior probability that it is in the other equilibrium. The results of performing this exercise for 5-6pm when I assume that clock strategy decisions are taken annually

[26]The LRTS is significant at the 5% level for 3-4am when clock strategy decisions are taken annually. The estimates would imply that there is a highly coordinated equilibrium where stations choose interval 2 with high probability in a very small proportion of markets ($\lambda = 0.96$). This result appears to be an anomaly.

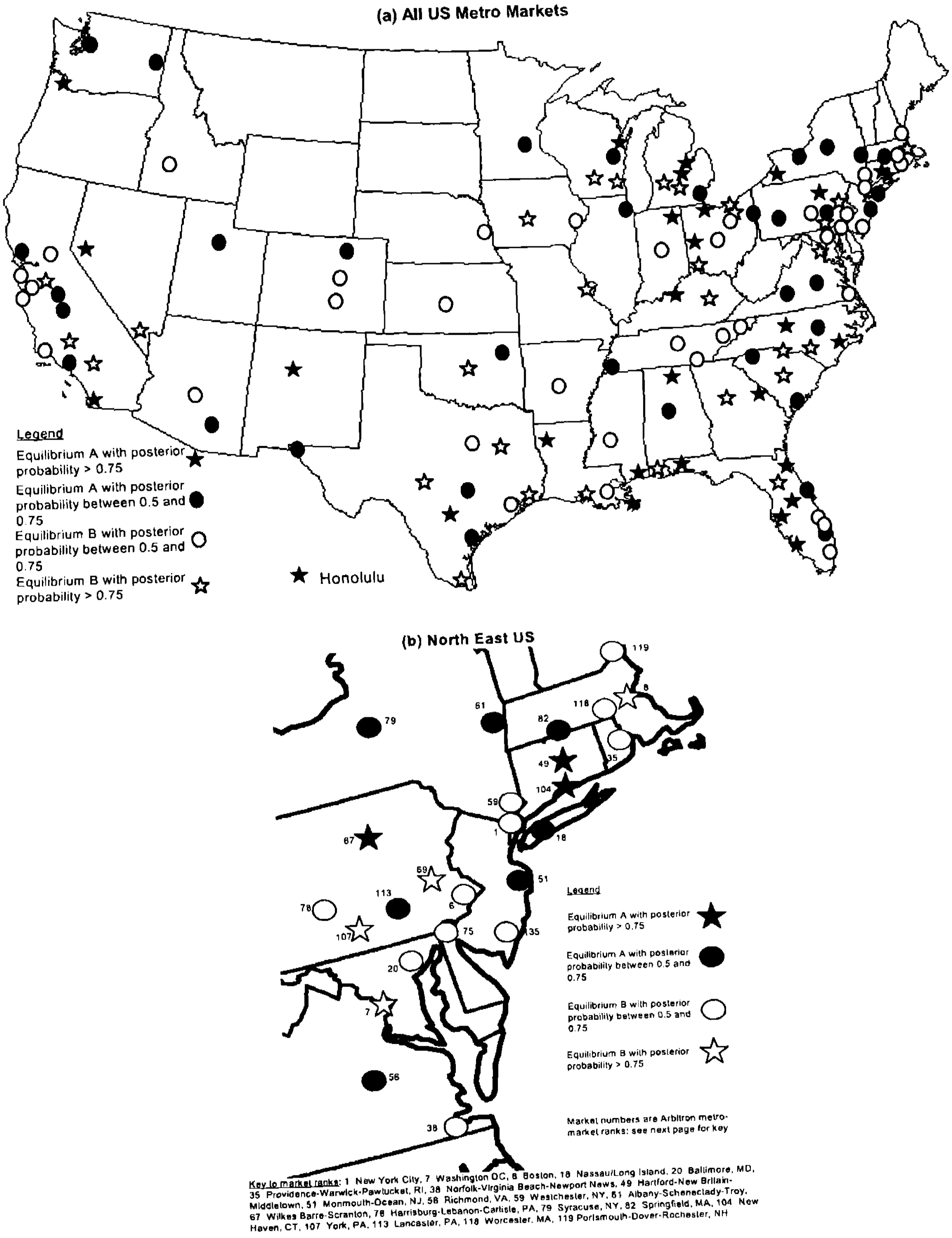
is shown in Figure 2-5(a) for the whole US and Figure 2-5(b) for the North East US where there are many markets close together. The filled shapes indicate markets classified into equilibrium A (coordinate on choosing interval 1), and the hollow shapes indicate markets classified into equilibrium B (coordinate on choosing interval 2).[27] As one would expect with $\widehat{\lambda} = 0.502$, the numbers of filled and hollow shapes are approximately equal. The stars represent markets that can be allocated to a particular equilibrium with posterior probability greater than 0.75.

Two features of the classification are of particular interest. First, more of the medium-sized and smaller markets can be allocated with greater confidence (more stars for these markets). For example, only 2 of the top 10 Arbitron markets (Washington DC (7), Boston (8)) and 3 of the markets ranked 11-20 (Atlanta (11), San Diego (17) and St. Louis (19)) are marked with stars. This is in spite of the fact that there are more stations in the data in larger markets which should allow them to be classified with greater confidence. 49% of the remaining markets are marked with stars, including 10 markets which have only two stations and so cannot be classified with a great deal of confidence (none of these have stars). This pattern is consistent with the results from testing for multiple equilibria separately in small and large markets in the basic model (Section 2.6.2).

Second, markets which are geographically close together appear to be more likely to be classified in the same equilibrium (e.g., Akron-Canton-Cleveland, Boston-Portsmouth-Providence-Worcester, Hartford-New Haven, San Francisco-San Jose) although there are exceptions (e.g., Los Angeles-Riverside, New York City-Nassau/Long Island). To understand why we might expect such markets to be in the same equilibrium consider the example of Boston, MA (market rank 8) and Worcester, MA (market rank 118). As can be seen in the Figure 2-5(b), Worcester is about 40 miles west of Boston. In Fall 2001 55.1% of rated listening in the Worcester market was to stations which are home to the Boston market. A Worcester listener switching between stations to avoid a commercial on a Worcester station could well include a number of Boston stations in her search. Therefore a Worcester station has an incentive to choose the same time for its commercial breaks as Boston stations as well as other Worcester stations, and in Figure 2-5(b) these markets are classified in the same equilibrium.

[27]There are some markets in which there is only one station. These markets can never be classified with a great deal of confidence and so they are not included on the maps.

Figure 2-5: Market Classification Based on the Annual Choice Clock Strategy Model 5-6pm



I examine the possibility that such markets tend to be in the same equilibrium by allowing equilibrium selection not to be independent across markets. I first identify markets (dependent markets) in which a significant share of rated radio listening (more than 20%) was attributed by Arbitron in Fall 2001 to stations in another larger (higher Arbitron rank) market (main markets).[28] The Bernoulli probability that a dependent market is in equilibrium A if its main market is in equilibrium A is λ_A, and the Bernoulli probability that a dependent market is in equilibrium B if its main market is in equilibrium B is λ_B. As before, λ is the Bernoulli probability that a non-dependent market is in equilibrium A. If a dependent market is disproportionately likely to be in the same equilibrium as its main market $\lambda_A > \lambda$ and $\lambda_B > 1 - \lambda$. Note that equilibrium selection in the dependent market is allowed to depend on the equilibrium in the main market but not the other way round. This is consistent with listening patterns. For example, while 55.1% of rated listening in Worcester in Fall 2001 was to Boston stations only 1.8% of rated listening in Boston was to Worcester stations and, indeed, only 6.1% was to stations from any market other than Boston. Thus while a Worcester station is likely to be concerned with coordinating with Boston stations, a Boston station is likely to be much less concerned with coordinating with Worcester stations.

Tables 2.8(a) and (b) reports the results of estimating this model when clock strategy decisions are taken annually and weekly respectively for the central drivetime hours 4-5pm and 5-6pm. In all of these estimates $\lambda_A > \lambda$ and $\lambda_B > 1 - \lambda$ as expected but the results are not statistically significant. This partly reflects two facts: the number of dependent markets is relatively small (there are 37 in the data) and many markets are not classified into a particular equilibrium with high probability. For the dependent markets this is partly because these markets are mainly relatively small with few stations in the data. In addition, several of the main markets are very large markets, such as New York City or Los Angeles, where the degree of coordination appears to be relatively low in which case the stations in the dependent markets may also have relatively low incentives to try to coordinate.[29]

[28]If, for a particular dependent market, more than one main market satisfies this criterion I treat the main market with the largest share of listening as the main market.

[29]If I do not use markets which are dependent on New York or Los Angeles the estimated λ_A and λ_B become even larger and slightly more significant although they are still not significant at any conventional significance level.

2.6.4 Model 3: Market Characteristics Affect the Incentive to Coordinate and Equilibrium Selection

The previous models have assumed that a station's payoff depends on the proportion of other stations in its market choosing the same time for a commercial break and that α, as well as β, is the same across markets. However, if the audience of a break actually depends on the number of stations which do not coordinate, rather than the proportion, then, because coordination is rarely perfect, there may be less incentive for an individual station to try to coordinate in a large market with many stations. This would be consistent with the evidence already presented that there are no multiple equilibria in the largest markets. In addition, stations in markets with more concentrated ownership may coordinate more because the positive externalities created by coordination should be partially internalized.

I allow market size and ownership concentration to affect coordination and equilibrium selection by making α and λ functions of these characteristics. HHI_m is the market HHI based on rated contemporary music stations which are home to market m. For market size I use either a dummy indicating whether the market is one of the 29 largest Arbitron markets ($LARGE_m$) or a count of the contemporary music stations which are home to the market ($NUMBER_m$). The data to calculate these variables comes from BIAfn's *Media Access Pro* database. Ownership data is monthly and I use format and listenership information reported from the Spring and Fall 2001 Arbitron surveys to identify the number of music stations. The average $NUMBER_m$ for the 146 markets in the sample is 12 (standard deviation 5) and the average HHI_m is 0.28 (standard deviation 0.16).

When I use the $LARGE_m$ dummy, α_m is simply

$$\alpha_m = \alpha_1 + \alpha_2 LARGE_m + \alpha_3 HHI_m \tag{2.40}$$

and α_1, α_2 and α_3 are parameters to be estimated. Characteristics affect λ_m, the Bernoulli probability that market m is in equilibrium A, through the logistic formula

$$\lambda_m = \frac{e^{\lambda_1 + \lambda_2 LARGE_m + \lambda_3 HHI_m}}{1 + e^{\lambda_1 + \lambda_2 LARGE_m + \lambda_3 HHI_m}} \tag{2.41}$$

and λ_1, λ_2 and λ_3 are parameters to be estimated.

As discussed in Section 2.3.4, the additional parameters are potentially identified if there are multiple equilibria although it may be that certain parameters cannot be identified. For example, if the incentive to coordinate in $LARGE_m$ markets cannot support multiple equilibria then λ_2 is not identified.

An EM algorithm could also be constructed to estimate this model (see Wang(1994) for examples of such algorithms). However, it was found to be more practical to use a Nelder-Mead simplex algorithm to maximize the likelihood directly. The likelihood appears to have multiple local maxima and to be quite flat in some regions of the parameter space so I use a grid search to find appropriate starting values. Multiple local maxima are a common problem in mixture models (McLachlan and Peel (2000), chp. 2). As this model is far more computationally demanding to estimate, because there are different equilibria in markets with different characteristics, I do not try to bootstrap this model to test for multiple equilibria.

Results

Tables 2.9(a) and 2.9(b) report the estimates for the two central drivetime hours 4-5pm and 5-6pm under the assumption that clock strategy decisions are taken weekly. Table 2.9(a) presents the results when the characteristics are HHI_m and $LARGE_m$. In both hours the α $LARGE_m$ coefficient is negative and large enough in absolute magnitude to indicate that multiple equilibria cannot be supported in $LARGE_m$ markets and the λ $LARGE_m$ coefficient is not identified.[30] Similarly, the implied incentive to coordinate (α) is greater in small markets than it was when small and large markets were combined in Table 6.[31] This provides further evidence that there is less coordination on timing in the largest markets. The α HHI_m coefficient is positive for 5-6pm but insignificant for both hours. However, even for 5-6pm, the coefficient implies that

[30]The standard error on the dummy is very large because once the estimated total value of α for a market is insufficient to support multiple equilibria the single equilibrium strategy is very insensitive to small changes in α. For example, for the 4-5pm estimates, the implied unique equilibrium probability of selecting interval 1 in the large markets is 0.507. If the estimated α dummy was -3.34 (rather than -1.34) the implied probability would be 0.503.

[31]For example, for the average HHI, the implied small market α is 5.3623 for 4-5pm compared with 5.316 in Table 6. The change in strategies is relatively modest: for example, the equilibrium A probability of choosing interval 1 for the clock strategy increases from 0.648 to 0.678.

ownership concentration has only a small effect on equilibrium strategies.[32] HHI_m does not appear to have a significant effect on equilibrium selection.

Table 2.9(b) presents the results when $LARGE_m$ is replaced by $NUMBER_m$, the number of rated contemporary music stations which are home to the market. The HHI_m variable remains the same as before. Multiple local maxima in the likelihood were a particular problem in estimating this model so the results should be interpreted with caution.[33] As in Table 9(a), the α HHI_m coefficients are insignificant and they are also very small in magnitude. The α $NUMBER_m$ coefficients are small and insignificant for both hours. Given the preceding results one would have expected this coefficient to be negative and significant. However, this may reflect the fact that the markets with the most contemporary music stations are not necessarily the largest markets. For example, the 5 markets with the highest $NUMBER_m$s in Fall 2001 were Chicago (ranked 3), Pittsburgh (23), Salt Lake City-Ogden (34), Albany-Schenectady-Troy (61) and Wilkes Barre-Scranton (67). In addition some markets with low $NUMBER_m$s are part of much larger urban areas where many out of market stations are available (for example, Westchester, NY has only 4 home music stations but access to many New York City stations).[34] The λ $NUMBER_m$ coefficient is large and significant for 4-5pm which suggests that the markets with the most home to market music stations are more likely to coordinate on interval 1. However, the other equilibrium selection coefficients are insignificant.

The conclusions from these estimates are clearly rather weak. However, the $LARGE_m$ results do suggest that, consistent with other results, there is less coordination on the timing of commercials in the largest markets. The HHI_m results do not provide significant evidence that more concentrated ownership leads to more coordination on timing even though common owners should internalize some of the externalities in the timing decision. There is little systematic evidence that market characteristics affect equilibrium selection.

[32]For example, a change in HHI from 0.2 to 0.3 would change the estimated 5-6pm small market equilibrium A probability of choosing interval 1 from 0.618 to 0.630.

[33]The estimates presented in Table 9(b) are based on using the coefficients in Table 7 as starting values with the additional characteristics parameters set to zero. A grid search failed to indicate that there were better starting values.

[34]I repeated the estimation replacing $NUMBER_m$ with the number of rated contemporary music stations whether home to the market or not. The coefficients on this number were negative but small and insignificant and I again encountered problems of multiple local maxima in the likelihood.

2.6.5 Model 4: An Extended Version of the Clock Strategy Model

I now present the results from estimating a more complicated version of the clock strategy model (Model 2) which takes some account of stations which do not have a clock strategy of having a commercial in either of the two intervals of interest and also allows the consistency of station timing choices to differ across clock strategies and equilibria. This lets me examine, for example, whether a station which does not typically have a commercial break in either of the two intervals of interest is nevertheless more likely to choose the interval on which other stations in its market coordinate if it does happen to have a commercial break.

To be precise, I allow a proportion ($P^{NOT1or2}$) of stations to have a clock strategy of not choosing either interval 1 or interval 2 for a commercial break.[35] This proportion is a parameter to be estimated and it is still assumed to be common across equilibria. However, I now allow the q-type probabilities, which reflect how consistently a particular timing interval is chosen, to differ across clock strategies and equilibria. For example, I estimate the probability that a station with an interval 1 clock strategy in an equilibrium A market has its commercial in that interval, the probability that it has it in interval 2 and the probability that it has a commercial break in neither of these intervals but at some other point during the hour. A different set of q-type probabilities are estimated for stations in equilibrium A but with a clock strategy of choosing interval 2, and a further set for stations in equilibrium A but with a clock strategy of choosing neither interval. These probabilities can be different for stations with other clock strategies or with the same clock strategy but in the other equilibrium. I estimate the model using an EM algorithm tailored to include the additional parameters.

Table 2.10 presents the results when the model is estimated for the two central drivetime hours, 4-5pm and 5-6pm. The results are interesting, if slightly difficult to interpret. In both of the hours about 30% of stations have clock strategies which do not involve having commercials in either interval (e.g., 0.298 for 5-6pm). These stations have commercials in one of the two intervals just over 10% of the time (e.g., for 5-6pm 0.093+0.021=0.114 in equilibrium A, 0.047+0.081=0.129 in equilibrium B) and when they do so they are more likely to choose the interval on which other stations are coordinating (e.g., for 5-6pm 0.093 compared with 0.021

[35]In estimating the simpler version of Model 2 all stations which ever have commercials in interval 1 or interval 2 were assumed to have either a strategy of choosing interval 1 or a strategy of choosing interval 2.

for equilibrium A). Stations choosing the coordinated interval for their clock strategy have a commercial in one of the intervals almost 90% of the time (e.g., for 5-6pm in an equilibrium A market, a station with an interval 1 clock strategy has a commercial in either interval 1 or interval 2 with probability 0.682+0.200=0.882) but actually choose the non-coordinated interval quite frequently (e.g., with probability 0.200 for the type of station just described). On the other hand, stations choosing the uncoordinated interval for their clock strategy choose the coordination interval more rarely (e.g., for 5-6pm in an equilibrium A market a station with an interval 2 clock strategy chooses interval 1 with probability 0.084). One possible explanation is that stations which do not coordinate are doing so because of a strong commitment to place some other form of programming, such as a traffic report, at the time when other stations are coordinating. This commitment precludes them from coordinating even though, absent this commitment, they would want to coordinate. An alternative explanation is that these stations deliberately choose to use a counter-programming strategy by not coordinating with other stations.[36] Without estimating a model which could explain why particular stations may want to adopt a counter-programming strategy it is hard to choose between these explanations.

The last part of the table provides the results from performing the bootstrap LRTS test for multiple equilibria in this model. The model with one equilibrium (results not reported) has 6 q parameters (these differ with a station's clock strategy). The presence of 8 additional parameters when I allow for multiple equilibria explains why the values of the LRTS for both the actual data and the bootstrap replications are much larger than in the earlier models. For 5-6pm the LRTS is significant at the 1% level, while for 4-5pm it is only significant at the 10% level. For the other drivetime hours the LRTS is also significant at the 1% level.

[36]An example of a station that might want to adopt an uncoordinated strategy is a new entrant which is trying to get listeners to sample its music and then stay, adopting it as their first choice station. An example in the programming literature is WAZU-FM, an Active Rock station in Dayton, OH which entered the format against an incumbent WTUE-FM. WAZU would not play commercials when WTUE was playing them and in fact would tell its listeners to try tuning to WTUE when WTUE was playing commercials and then promise them that WAZU would play less commercials than WTUE (Lynch and Gillespie (1998)). An interesting anecdote is that in my data (some years after this event) WAZU and WTUE are both unusual stations in having disproportionately many commercial breaks in the first 15 minutes of drivetime hours. This suggests that by 2001 WAZU's incentives may have changed, at least to some extent, to wanting to coordinate with WTUE.

2.7 Conclusion

Many models with interesting interactions between agents have multiple equilibria. In applied work, this multiplicity has either been largely ignored (e.g., the social interactions literature) or been seen as creating an estimation problem (e.g., the entry game literature). Common responses to this estimation problem, such as changing the model to guarantee uniqueness, are unsatisfactory if it is plausible, as it surely often is, that the data contains observations from different equilibria. The central ideas in this paper are that it is possible to identify different equilibria in the data and, moreover, that the existence of multiple equilibria can actually help to identify the parameters. The logic is that if there are multiple equilibria we can rule out parameters which can only support some of the equilibria. I illustrate this idea using a simple game in which the parameters are only separately identified if there are multiple equilibria both in the game and in the data. I show how standard techniques from the statistics literature on dealing with mixtures of distributions can be used to explicitly estimate the different equilibria when we cannot observe directly which equilibrium each observation is from. The kind of explicit treatment of multiple equilibria and equilibrium selection presented here could clearly be very useful in other settings where, for example, it might be important to understand whether a new policy might change the equilibrium that a market is in. Of course, in more complicated models, it may be necessary to develop new techniques to identify and estimate the different possible equilibria: this provides one important direction for future research.

This paper also provides an application using a new dataset on the timing of commercial breaks by music radio stations. A station, which sells the audience of its commercial breaks to advertisers, has an incentive to play its commercials at the same times as other stations in its market to reduce the number of listeners who avoid its commercials by switching to music on other stations. However, while stations do tend to play commercials at the same time (Figure 2-1), this could also be explained by other factors, such as Arbitron's methodology for estimating station ratings. I find significant evidence of multiple equilibria, allowing the incentive to coordinate to be identified, during drivetime hours when the incentive is strongest because in-car listeners can switch stations easily. This finding is robust to a number of specifications. However, while the incentive to coordinate is strong enough to create multiple equilibria during drivetime, the implied degree of coordination in Nash equilibrium is relatively modest. This is equivalent to saying that much of the pattern in Figure 2-1 is explained by factors such as Arbitron's methodology. The lack of coordination in actual timing is partly explained by the fact that it is practically quite hard for stations to consistently play commercials at their scheduled times. However, I find that coordination in the choice of scheduled times for commercials is also relatively modest, although greater than coordination in actual timing. The lack of coordination appears to be particularly marked in the largest radio markets possibly because they have so many stations that a listener who really wants to avoid commercials can almost always do so. One explanation for the lack of coordination in Nash equilibrium is that an individual station does not internalize how its timing affects the audience of commercials on other stations. Consistent with this, my parameter estimates imply that coordination would be almost perfect if stations maximized their expected joint payoffs. The obvious question is whether this failure to coordinate has a significant impact on industry revenues. While I do not have the data to calculate the exact relationship between audiences, revenues and timing, a simple and conservative "back of the envelope" calculation suggests that the impact is probably large. Annual radio advertising revenues are about \$20 billion (Radio Advertising Bureau (2003)). In-car listeners, accounting for 34% of all listening (Arbitron and Edison Media Research (2003)), were found by Abernethy (1991) to avoid, on average, about 50% of the commercials they would hear if they did not switch stations. Suppose that only in-car listeners avoid commercials and that closer coordination would result in them avoiding 45%, rather than 50%, of commercials then, if revenues were to increase proportionally with the number of listeners to commercials, industry revenues would rise by about \$220 million. If stations could coordinate very closely then avoidance of commercials might fall by more and the resulting increase in revenues would be even greater.

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Appendix: Estimation Procedures

This Appendix provides more details of the estimation procedures used for the different models.

Estimation of the Basic Model with Multiple Equilibria

With two equilibria, the equilibrium choice probabilities of choosing interval 1 are $p_A^*(\beta, \alpha)$ and $p_B^*(\beta, \alpha)$ with $p_A^*(\beta, \alpha) \geq p_B^*(\beta, \alpha)$. The likelihood of the incomplete data can be written

$$L = \prod_{m=1}^{M} \frac{(n_{m1} + n_{m2})!}{n_{m1}! n_{m2}!} \left\{ \begin{array}{c} \lambda p_A^*(\beta, \alpha)^{n_{m1}} (1 - p_A^*(\beta, \alpha))^{n_{m2}} \\ +(1 - \lambda) p_B^*(\beta, \alpha)^{n_{m1}} (1 - p_B^*(\beta, \alpha))^{n_{m2}} \end{array} \right\} \tag{2.42}$$

Maximizing the log-likelihood with respect to the parameters λ, β and α gives first-order conditions which, respectively, can be written as

$$\sum_{m=1}^{M} \frac{\tau_m}{\lambda} - \frac{(1 - \tau_m)}{(1 - \lambda)} = 0 \tag{2.43}$$

$$\sum_{m=1}^{M} \left(\begin{array}{c} \frac{n_{m1} \tau_m \frac{\partial p_A^*(\beta,\alpha)}{\partial \beta}}{p_A^*(\beta,\alpha)} - \frac{n_{m2} \tau_m \frac{\partial p_A^*(\beta,\alpha)}{\partial \beta}}{(1-p_A^*(\beta,\alpha))} + \\ \frac{n_{m1}(1-\tau_m) \frac{\partial p_B^*(\beta,\alpha)}{\partial \beta}}{p_B^*(\beta,\alpha)} - \frac{n_{m2}(1-\tau_m) \frac{\partial p_B^*(\beta,\alpha)}{\partial \beta}}{(1-p_B^*(\beta,\alpha))} \end{array} \right) = 0 \tag{2.44}$$

$$\sum_{m=1}^{M} \left(\begin{array}{c} \frac{n_{m1} \tau_m \frac{\partial p_A^*(\beta,\alpha)}{\partial \alpha}}{p_A^*(\beta,\alpha)} - \frac{n_{m2} \tau_m \frac{\partial p_A^*(\beta,\alpha)}{\partial \alpha}}{(1-p_A^*(\beta,\alpha))} + \\ \frac{n_{m1}(1-\tau_m) \frac{\partial p_B^*(\beta,\alpha)}{\partial \alpha}}{p_B^*(\beta,\alpha)} - \frac{n_{m2}(1-\tau_m) \frac{\partial p_B^*(\beta,\alpha)}{\partial \alpha}}{(1-p_B^*(\beta,\alpha))} \end{array} \right) = 0 \tag{2.45}$$

where τ_m is the conditional probability (given that data and parameters) that observation m comes from the A equilibrium (this is also known as the posterior probability), i.e.,

$$\tau_m = \frac{\lambda p_A^*(\beta, \alpha)^{n_{m1}} (1 - p_A^*(\beta, \alpha))^{n_{m2}}}{\lambda p_A^*(\beta, \alpha)^{n_{m1}} (1 - p_A^*(\beta, \alpha))^{n_{m2}} + (1 - \lambda) p_B^*(\beta, \alpha)^{n_{m1}} (1 - p_B^*(\beta, \alpha))^{n_{m2}}} \tag{2.46}$$

As described in the text, the EM algorithm exploits the fact that the solution to (2.43)-(2.45) is also a solution to iterating a two-step "Expectation(E)-Maximization(M)" procedure. The E-step takes the conditional expectation of (2.35) by replacing the Z_m^As with $\widehat{\tau}_m^A$ which is τ_m evaluated at the current iterated parameter values $(\widehat{\beta}, \widehat{\alpha}, \widehat{\lambda})$. Ignoring the binomial constant, this expectation is

$$E(\ln L_c) = \sum_{m=1}^{M} \left(\begin{array}{c} \widehat{\tau}_m^A \left[\ln \widehat{\lambda} + n_{m1} \ln p_A^*(\widehat{\beta}, \widehat{\alpha}) + n_{m2} \ln(1 - p_A^*(\widehat{\beta}, \widehat{\alpha}))\right] + \\ (1 - \widehat{\tau}_m^A) \left[\ln(1 - \widehat{\lambda}) + n_{m1} \ln p_B^*(\widehat{\beta}, \widehat{\alpha}) + n_{m2} \ln(1 - p_B^*(\widehat{\beta}, \widehat{\alpha}))\right] \end{array} \right) \tag{2.47}$$

The M-step involves maximizing (2.47) with respect to the parameters $\widehat{\lambda}, \widehat{\beta}$ and $\widehat{\alpha}$. The new estimate of $\widehat{\lambda}$, $\widehat{\widehat{\lambda}}$, has a simple form

$$\widehat{\widehat{\lambda}} = \frac{\sum_{m=1}^{M} \widehat{\tau}_m}{M} \tag{2.48}$$

I use two alternative approaches to maximizing (2.47) with respect to $\widehat{\beta}$ and $\widehat{\alpha}$. The first approach involves directly maximizing (2.47) using a Nelder-Mead simplex technique to give new estimates $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\alpha}}$ (these do not have simple analytic forms).[37] Equilibrium strategies $p^*_A(\beta,\alpha)$ and $p^*_B(\beta,\alpha)$ are found by iterating best responses to find fixed points. The E- and M-steps are iterated (updating $\widehat{\tau}$ given the new parameter estimates produced by the M-step) until the incomplete data log-likelihood converges giving the MLE for (β,α,λ).[38]

The second approach to maximizing (2.47) is indirect. I maximize (2.47) with respect to p^*_A and p^*_B rather than β and α. $\widehat{\widehat{p^*_A}}$ and $\widehat{\widehat{p^*_B}}$ have simple analytic forms:

$$\widehat{\widehat{p^*_A}} = \frac{\sum_{m=1}^{M} \widehat{\tau}_m n_{m1}}{\sum_{m=1}^{M} \widehat{\tau}_m (n_{m1} + n_{m2})} \tag{2.49}$$

$$\widehat{\widehat{p^*_B}} = \frac{\sum_{m=1}^{M} (1-\widehat{\tau}_m) n_{m1}}{\sum_{m=1}^{M} (1-\widehat{\tau}_m)(n_{m1} + n_{m2})} \tag{2.50}$$

$\widehat{\widehat{p^*_A}}$ is a weighted average of the proportion of stations having their commercials in interval 1 with more weight placed on observations that are more likely to come from equilibrium A. The E- and M-steps are again iterated until convergence of the incomplete data log-likelihood. The final estimates of $\widehat{p^*_A}$ and $\widehat{p^*_B}$ are substituted into

$$\ln\left(\frac{\widehat{p^*_A}}{1-\widehat{p^*_A}}\right) = \widehat{\beta} + \widehat{\alpha}(2\widehat{p^*_A} - 1) \tag{2.51}$$

$$\ln\left(\frac{\widehat{p^*_B}}{1-\widehat{p^*_B}}\right) = \widehat{\beta} + \widehat{\alpha}(2\widehat{p^*_B} - 1) \tag{2.52}$$

(which come from rewriting (2.4)) to solve analytically for $\widehat{\beta}$ and $\widehat{\alpha}$. ($\widehat{\beta}$,$\widehat{\alpha}$) will support $\widehat{p^*_A}$ and $\widehat{p^*_B}$ as equilibria but not necessarily stable equilibria. I therefore check whether ($\widehat{\beta}$,$\widehat{\alpha}$) support $\widehat{p^*_A}$ and $\widehat{p^*_B}$ as stable equilibria: if they do then the MLE of ($\widehat{\beta}$,$\widehat{\alpha}$) have been found and are the same MLE as would be produced by the direct method; if they do not then the functional form restrictions described in Section 2.4 bind and the direct method, which implicitly maximizes over only those $\widehat{p^*_A}$ and $\widehat{p^*_B}$ which can be supported as stable equilibria must be used. The advantage of the indirect method is that it is much quicker to implement because it uses analytic solutions. With the actual data this method was therefore tried first and the direct method was then used if the resultant ($\widehat{\beta}$,$\widehat{\alpha}$) did not support multiple equilibria.[39] As explained in Section 2.4 when calculating bootstrap values of the LRTS I use, when estimating under the alternative hypothesis that there may be multiple equilibria, the value of the maximized log-likelihood from

[37]The non-derivative Nelder-Mead technique is well-suited to this problem because at the boundary in parameter space between the (β,α) pairs which support multiple equilibria and the pairs which support a single equilibrium the likelihood function is not continuous.

[38]Dempster et al. (1977) show that an EM iteration always increases the value of the likelihood so convergence is guaranteed when the likelihood is bounded above as it is here.

[39]This happens typically for the non-drivetime hours when my results suggest that there are no multiple equilibria.

the indirect method whether or not the resulting values $\widehat{p_A^*}$ and $\widehat{p_B^*}$ can be supported as stable equilibria. This log-likelihood should not be less than the value of the maximized log-likelihood from the direct method. The greater speed of the indirect method allows a greater number of bootstraps to be performed.

It is well-known that the likelihood of mixture models can have multiple local maxima and that convergence of the EM algorithm can be slow (see McLachlan and Peel (2000), chp. 2). In practice the indirect method of EM always seemed to converge quite quickly to the same estimates from a number of different starting points when there was evidence of multiple equilibria (using both actual and simulated data).[40] The direct method can be slow reflecting the need to use Nelder-Mead to perform the maximization in each iteration, although it also appeared to converge consistently to the same parameter values. To reduce the time required for the direct method I perform an initial rough grid search over the values of β and α which support multiple equilibria in order to identify good starting values. In addition, in each M-step, I first compute a new estimate of $\widehat{\lambda}$, then perform another E-step before using Nelder-Mead to maximize with respect to $\widehat{\beta}$ and $\widehat{\alpha}$.

EM Estimation for Model 2

I also use an EM algorithm to estimate Model 2 (stations make infrequent clock strategy decisions which are implemented with noise) which has an additional parameter q representing the probability that the clock strategy interval is actually chosen on a particular day. The clock strategy is not observed and is handled in a similar way to the unobserved identity of the equilibrium in the basic model. Consider the problem when there is only a single equilibrium and stations make clock strategy decisions each week, choosing interval 1 for the clock strategy with probability p^*. The (incomplete data) likelihood can be written as

$$L = \prod_{m=1}^{M} \prod_{i=1}^{N_m} \frac{(n_{i1}+n_{i2})!}{n_{i1}!n_{i2}!} \left[p^*(\beta,\alpha,q)q^{n_{i1}}(1-q)^{n_{i2}} + (1-p^*(\beta,\alpha,q))(1-q)^{n_{i1}}q^{n_{i2}}\right] \tag{2.53}$$

where N_m is the number of stations observed having commercials in either of the intervals at some point in market-week m, M is the number of market-weeks in the data and n_{i1} and n_{i2} are the number of times station i is observed having a break in intervals 1 and 2 respectively. If Y_i^1 is an indicator which takes value 1 if i's clock strategy is to choose interval 1 then, ignoring the binomial constant, the complete data log-likelihood is

$$\ln L_c = \sum_{m=1}^{M} \sum_{i=1}^{N_m} \left(\begin{array}{c} Y_i^1[\ln p^*(\beta,\alpha,q) + n_{i1}\ln q + n_{i2}\ln(1-q)] \\ +(1-Y_i^1)[\ln(1-p^*(\beta,\alpha,q)) + n_{i2}\ln q + n_{i1}\ln(1-q)] \end{array} \right) \tag{2.54}$$

The expectation of the complete data log likelihood is formed in the E-step by replacing the Y_i^1s by $\widehat{\tau}_i$, the conditional probability that station i has an interval 1 clock strategy given the data and current estimates of the parameters. With a single equilibrium, β and α are not

[40] In the case of data with no multiple equilibria the algorithm could converge to different points in the non-identified set of parameters depending on the starting point.

separately identified so I proceed by estimating $\widehat{p^*}$ and $\widehat{q}$. In this case,

$$\widehat{\tau}_i = \frac{\widehat{p^*}\widehat{q}^{n_{i1}}(1-\widehat{q})^{n_{i2}}}{\widehat{p^*}\widehat{q}^{n_{i1}}(1-\widehat{q})^{n_{i2}} + (1-\widehat{p^*})(1-\widehat{q})^{n_{i1}}\widehat{q}^{n_{i2}}} \tag{2.55}$$

The M-step computes new estimates of p^* and q, $\widehat{\widehat{p^*}}$ and $\widehat{\widehat{q}}$, which have simple analytic forms

$$\widehat{\widehat{p^*}} = \frac{\sum_{m=1}^{M}\sum_{i=1}^{N_m}\widehat{\tau}_i}{\sum_{m=1}^{M}N_m} \tag{2.56}$$

$$\widehat{\widehat{q}} = \frac{\sum_{m=1}^{M}\sum_{i=1}^{N_m}\widehat{\tau}_i n_{i1} + n_{i2}(1-\widehat{\tau}_i)}{\sum_{m=1}^{M}\sum_{i=1}^{N_m} n_{i1} + n_{i2}} \tag{2.57}$$

The E- and M-steps are iterated to convergence. If I assume that $\alpha = 0$ then MLE for $\widehat{\beta}$ is given by $\ln\left(\frac{\widehat{p^*}}{1-\widehat{p^*}}\right)$. Estimation of the model with more than one equilibrium allowed is done by straightforward extensions to the direct and indirect methods from the basic model which reflect the fact that both the equilibrium and the clock strategy of the stations are unknown. As with the basic model, the algorithm seemed to converge quite reliably to the same estimates when there was evidence of multiple equilibria.

q is identified from within station variation in timing (q will be high if stations tend to have the same timing every day). Obviously we want to constrain q to be greater than $\frac{1}{2}$ (so that a station's clock strategy interval is chosen more frequently than the other interval). However, it is not necessary to explicitly impose this constraint as long as the starting value of q is greater than $\frac{1}{2}$.

I also use a straightforward development of the approach described here to estimate Model 4 which contains a much greater number of q-type parameters.

Estimation for Model 3

An EM-style algorithm could also be constructed to estimate the model with characteristics affecting α and λ (see Wang (1994) for examples of EM-style algorithms for mixed regression models with discrete data in other settings). However, after some experimentation, it was found to be more practical to use a grid search to find reasonable starting values and then to use the Nelder-Mead simplex algorithm to directly compute ML estimates of the parameters. This requires finding the equilibrium in each market, given the parameters and the characteristics of the market, which is done by iterating best responses to find fixed points. In estimation, I encountered particular problems of multiple local maxima in the likelihood when estimating the models including the number of stations.

Standard Errors

For the basic model with one equilibrium the expected value of the information matrix can be found analytically when it is assumed that $\alpha = 0$. Apart from this case, standard errors are estimated using either a bootstrap or the BHHH or "outer product of the gradients" method (Greene (1997), p. 139) with gradients with respect to the parameters computed numerically. When models with multiple equilibria are estimated but the estimated parameters are in the subset where the parameters are not identified I do not present standard errors as they would have little meaning (the likelihood function is flat within the subset). In the case where the MLE are not in this subset but the true parameters are the standard errors might not be suitable for inference as the parameter estimates may have non-standard distributions. I do not try to deal with this issue here as I do not rely on the estimated standard errors for inference.

Table 2.4: Basic Model Results - Each Market-Day is an Independent Repetition of the Game

	Afternoon Drivetime Hours				Non-Drivetime Hours			
	3-4pm	4-5pm	5-6pm	6-7pm	3-4am	12-1pm	9-10pm	10-11pm
Model with one equilibrium								
β	0.217 (0.012)	0.091 (0.012)	0.061 (0.011)	0.257 (0.012)	0.226 (0.015)	0.101 (0.012)	-0.072 (0.012)	-0.024 (0.012)
Log Likelihood	-20449.0	-20741.5	-21292.2	-19992.8	-12053.6	-20052.3	-18867.9	-17990.1
Implied probability of choosing interval 1	0.554	0.523	0.515	0.564	0.556	0.525	0.482	0.494
Model with two equilibria								
β	0.001 (0.002)	0.001 (0.002)	-0.001 (0.001)	0.001 (0.001)	0	0	-0.000 (0.001)	0
α	2.019 (0.010)	2.017 (0.009)	2.017 (0.006)	2.018 (0.005)	2.009	2.002	2.005 (0.010)	2.000
λ	0.689 (0.091)	0.498 (0.132)	0.777 (0.076)	0.786 (0.083)	1	1	0.460 (0.145)	0
Log Likelihood	-20441.6	-20732.4	-21286.5	-19989.0	-12053.6	-20052.3	-18867.4	-17990.1
Implied probabilities of choosing interval 1								
Nash equilibria strategies	0.596,0.461	0.591,0.456	0.547,0.408	0.593,0.472	0.556	0.525	0.543,0.456	0.494
Joint expected payoff maximizing strategies	0.980	0.980	0.020	0.980	-	-	-	-
Number of market-days	7,616	7,672	7,750	7,654	6,551	7,616	7,528	7,405
Number of station-days	29,752	29,968	30,739	29,187	17,551	28,983	27,246	25,957
Test for Multiple Equilibria								
LR test statistic	14.6	18.2	11.5	7.5	0.0	0.0	0.8	0.0
Bootstrapped LRTS Distribution Quantiles (499 replications, see Section 2.4)								
90th percentile	2.7	3.4	2.7	2.8	3.2	2.8	3.2	2.7
95th percentile	4.5	4.7	4.1	4.1	4.7	4.0	5.2	4.2
99th percentile	8.0	7.4	7.5	8.0	7.4	6.0	7.4	6.7

Notes:
1. Standard errors computed using a bootstrap allowing for correlation across days from the same market in parentheses
2. Number of station-days is the number of station-hour observations in which the station has a commercial in either interval 1 or interval 2. A market-day observation has at least one home to market station with a commercial in one of the two intervals.
3. Calculated log-likelihoods do not include binomial coefficients which are constants independent of the parameters and the number of equilibria.

Table 2.5: Likelihood Ratio Test Statistic Results for the Basic Model Estimated Separately for Large and Small Metro-Markets

	Afternoon Drivetime Hours				Non-Drivetime Hours			
	3-4pm	4-5pm	5-6pm	6-7pm	3-4am	12-1pm	9-10pm	10-11pm
Largest markets (Arbitron Rank 1-29)								
Number of market-days	1,599	1,598	1,598	1,594	1,532	1,585	1,576	1,561
Number of station-days	8,877	9,167	9,716	9,145	5,681	8,766	8,389	7,986
LR Test Statistic	0.3	0.1	0.0	0.0	0.0	0.0	4.2	0.01
Bootstrapped LRTS Distribution Quantiles								
(499 replications, see Section 2.4)								
90th percentile	3.0	3.0	3.0	3.0	3.5	3.4	3.4	2.9
95th percentile	4.1	4.6	4.3	4.7	4.6	5.5	4.9	4.2
99th percentile	7.4	7.9	9.1	7.4	7.5	8.4	9.3	8.7
Smaller markets (Arbitron Rank 30+)								
Number of market-days	6,017	6,074	6,152	6,060	5,019	6,031	5,952	5,844
Number of station-days	20,875	20,801	21,023	20,042	11,870	20,217	18,857	17,971
LR Test Statistic	18.2	22.7	18.2	13.1	0.3	0	0	0
Bootstrapped LRTS Distribution Quantiles								
(499 replications, see Section 2.4)								
90th percentile	2.5	3.0	2.2	2.6	2.6	2.8	2.8	2.8
95th percentile	4	4.5	3.6	4	3.9	4.4	4.6	4.1
99th percentile	8.3	9.6	6.3	6.2	6.6	7.9	8.0	6.6

Notes
1. Station-days and market-days as defined in Table 2.4

Table 2.6: Model 2 Results - Stations Make Weekly Clock Strategy Decisions Which Are Implemented With Noise

	Afternoon Drivetime Hours				Non-Drivetime Hours			
	3-4pm	4-5pm	5-6pm	6-7pm	3-4am	12-1pm	9-10pm	10-11pm
Model with one equilibrium								
β	0.410 (0.024)	0.170 (0.024)	0.107 (0.024)	0.435 (0.025)	0.477 (0.034)	0.209 (0.026)	-0.001 (0.026)	0.070 (0.028)
q	0.809 (0.002)	0.810 (0.002)	0.808 (0.002)	0.802 (0.002)	0.789 (0.004)	0.801 (0.003)	0.803 (0.003)	0.794 (0.003)
Log Likelihood	-18208.2	-18377.9	-18931.1	-18064.3	-11193.0	-18050.9	-16974.3	-16074.4
Implied probabilities of choosing interval 1	0.601	0.542	0.527	0.607	0.617	0.552	0.500	0.518
Model with two equilibria								
β	0.007 (0.004)	0.005 (0.004)	0.002 (0.005)	0.006 (0.004)	0.000 (0.286)	0.000 (0.121)	0.000 (0.007)	-0.000 (0.010)
α	5.447 (0.059)	5.316 (0.086)	5.344 (0.101)	5.673 (0.113)	6.099 (3.564)	5.532 (3.061)	5.485 (0.101)	5.799 (0.381)
q	0.807 (0.007)	0.810 (0.006)	0.808 (0.007)	0.801 (0.003)	0.789 (0.003)	0.801 (0.003)	0.803 (0.003)	0.794 (0.003)
λ	0.739 (0.177)	0.530 (0.217)	0.528 (0.296)	0.751 (0.166)	0.990 (0.337)	0.990 (1.902)	0.501 (1.885)	0.990 (1.307)
Log Likelihood	-18197.3	-18365.2	-18923.2	-18056.7	-11193.0	-18050.9	-16973.7	-16074.4
Implied probabilities of choosing interval 1								
Nash equilibria strategies	0.665,0.415	0.648,0.425	0.621,0.425	0.665,0.432	0.618,0.384	0.553,0.451	0.554,0.445	0.518,0.482
Joint expected payoff maximizing strategies	0.982	0.981	0.980	0.982	-	-	-	-
Number of market-weeks	1,633	1,648	1,661	1,649	1,550	1,627	1,630	1,619
Number of station-weeks	8,838	8,896	9,121	8,892	6,715	8,759	8,606	8,427
Test for Multiple Equilibria								
LR test statistic	21.7	25.3	15.9	15.1	0.1	0.0	1.4	0.0
Bootstrapped LRTS Distribution Quantiles (499 replications, see Section 2.4)								
90th percentile	1.2	1.3	1.7	1.3	1.8	1.6	1.6	1.9
95th percentile	2.1	2.2	3.0	2.2	2.7	2.5	2.8	3.2
99th percentile	4.9	5.9	5.6	4.3	5.6	4.4	5.4	7.0

Notes:
1. Standard errors computed using a bootstrap in parentheses
2. A station-week observation is one in which the station has at least one commercial in either of the two intervals at least one day during the week.
A market-week observation has at least one home to market station with at least one commercial in one of the two intervals at least one day during the week.
3. Calculated log-likelihoods do not include binomial coefficients which are constants independent of the parameters and the number of equilibria.

Table 2.7: Model 2 Results - Stations Make Annual Clock Strategy Decisions Which Are Implemented With Noise

	Afternoon Drivetime Hours				Non-Drivetime Hours			
	3-4pm	4-5pm	5-6pm	6-7pm	3-4am	12-1pm	9-10pm	10-11pm
Model with one equilibrium								
β	0.511 (0.060)	0.250 (0.054)	0.152 (0.058)	0.506 (0.058)	0.658 (0.072)	0.302 (0.068)	0.257 (0.068)	0.313 (0.071)
q	0.752 (0.001)	0.752 (0.001)	0.747 (0.001)	0.745 (0.001)	0.736 (0.002)	0.740 (0.001)	0.743 (0.001)	0.743 (0.002)
Log Likelihood	-17243.9	-17377.9	-17987.0	-17154.9	-10593.4	-17198.9	-16098.5	-15353.9
Implied probabilities of choosing interval 1	0.625	0.562	0.538	0.624	0.658	0.575	0.564	0.578
Model with two equilibria								
β	0.009 (0.006)	0.011 (0.028)	0.006 (0.004)	0.000 (0.030)	-0.068 (0.026)	0.001 (0.010)	0.001 (0.004)	0
α	8.187 (0.353)	8.223 (0.476)	8.415 (0.615)	8.625 (0.612)	10.266 (3.018)	8.772 (0.240)	8.514 (0.269)	8.5214
q	0.752 (0.005)	0.752 (0.006)	0.747 (0.010)	0.745 (0.006)	0.736 (0.004)	0.740 (0.005)	0.743 (0.005)	0.743
λ	0.770 (0.110)	0.544 (0.167)	0.502 (0.124)	0.882 (0.104)	0.960 (0.162)	0.831 (1.533)	0.874 (4.413)	1
Log Likelihood	-17240.1	-17369.6	-17983.4	-17150.0	-10591.9	-17198.8	-16098.5	-15353.9
Implied probabilities of choosing interval 1								
Nash equilibria strategies	0.685,0.405	0.695,0.400	0.660,0.418	0.667,0.334	0.676,0.175	0.600,0.449	0.575,0.464	0.6
Joint expected payoff maximizing strategies	0.982	0.983	0.981	0.982	-	-	-	-
Number of market-years	144	145	145	145	144	144	145	144
Number of station-years	1,000	1,006	1,009	1,003	942	1,010	1,010	1,016
Test for Multiple Equilibria								
LR test statistic	7.5	16.6	7.1	9.9	3.0	0.3	0.0	0.0
Bootstrapped LRTS Distribution Quantiles (499 replications, see Section 2.4)								
90th percentile	1.1	1.3	1.5	1.4	1.4	1.4	1.8	1.1
95th percentile	1.9	2.0	2.1	2.3	2.7	2.5	2.8	2.3
99th percentile	4.9	4.9	5.1	5.5	6.7	5.1	6.0	6.4

Notes:
1. Standard errors computed using a bootstrap in parentheses
2. A station-year observation is one in which the station has at least one commercial in either of the two intervals at least one day during the year.
A market-year observation has at least one home to market station with at least one commercial in one of the two intervals at least one day during the year.
There are 1,063 stations in the data but, in each hour, some of these stations never have a commercial in the two intervals.
3. Calculated log-likelihoods do not include binomial coefficients which are constants independent of the parameters and the number of equilibria.

Table 2.8: Equilibrium Selection in Dependent Markets

(a) Station Clock Strategies Chosen Annually

	4-5pm	5-6pm
β	0.011 (0.008)	0.006 (0.008)
α	8.223 (0.207)	8.416 (0.259)
q	0.752 (0.001)	0.747 (0.001)
λ	0.547 (0.193)	0.497 (0.326)
λ_A	0.760 (0.582)	0.915 (0.612)
λ_B	0.880 (0.612)	0.998 (0.495)
Log Likelihood	-17368.9	-17982.6
Number of market-years	1,648	1,661
Number of station-years	8,896	9,121

(b) Station Clock Strategies Chosen Weekly

	4-5pm	5-6pm
β	0.005 (0.005)	0.003 (0.004)
α	5.318 (0.113)	5.347 (0.096)
q	0.810 (0.003)	0.809 (0.004)
λ	0.536 (0.207)	0.465 (0.252)
λ_A	0.744 (0.325)	0.883 (0.366)
λ_B	0.684 (0.285)	0.865 (0.253)
Log Likelihood	-18364.8	-18922.1
Number of market-weeks	1,648	1,661
Number of station-weeks	8,896	9,121

1. Standard errors computed using BHHH method in parentheses
2. Market-years and station-years as defined in Table 2.7
3. Market-weeks and station-weeks as defined in Table 2.6
4. Calculated log-likelihoods do not include binomial coefficients which are constants independent of the parameters.

Table 2.9: Model 3 Results - Parameters Included in α and λ

(a) Dummy for Large Markets

	4-5pm	5-6pm
β	0.0079 (0.0088)	-0.0079 (0.0063)
Parameters of α		
Constant	5.3668 (0.1565)	5.3953 (0.0192)
Large market dummy (Arbitron rank <30)	-1.3493 (2.0444)	-5.3953 (29.166)
Market HHI	-0.0150 (0.2256)	0.1489 (0.2136)
Parameters of λ		
Constant	-0.5222 (0.7870)	0.9826 (0.4768)
Large market dummy (Arbitron rank <30)	-	-
Market HHI	3.2455 (2.1361)	0.9698 (1.8688)
q	0.8102 (0.0025)	0.8090 (0.0013)
Log Likelihood	-18353.5	-18902.2
Number of market-weeks	1,648	1,661
Number of station-weeks	8,896	9,121

(b) Number of Home Music Stations

	4-5pm	5-6pm
β	0.0034 (0.0006)	0.0026 (0.0045)
Parameters of α		
Constant	5.3428 (0.0398)	5.3455 (0.0878)
Number of Home Music Stations	0.0023 (0.0021)	0.0003 (0.0031)
Home Music Station HHI	0.0050 (0.0376)	0.0004 (0.0844)
Parameters of λ		
Constant	-3.2055 (1.4787)	0.1104 (1.4702)
Number of Home Music Stations	0.2480 (0.0704)	0.0007 (0.0578)
Home Music Station HHI	-0.0078 (2.8557)	-0.0011 (2.158)
q	0.8085 (0.0011)	0.8082 (0.0020)
Log Likelihood	-18343.7	-18915.7
Number of market-weeks	1,648	1,661
Number of station-weeks	8,896	9,121

1. Standard errors computed using BHHH method in parentheses
2. Market-weeks and station-weeks as defined in Table 2.6
3. Calculated log-likelihoods do not include binomial coefficients which are constants independent of the parameters.

Table 2.10: Model 4 - An Extended Version of the Clock Strategy Model

	4-5pm	5-6pm
Model with two equilibria		
Parameters affecting strategy choices		
$P^{NOT\ 1\ OR\ 2}$	0.322 (0.005)	0.298 (0.005)
β	-0.014 (0.035)	-0.123 (0.034)
α	4.507 (1.230)	6.884 (0.971)
λ	0.396 (0.029)	0.497 (0.028)
Implied Nash equilibria probabilities of choosing interval 1 as clock strategy	0.372,0.322	0.377,0.278
Parameters reflecting probability of actual timing conditional on clock strategies and the equilibrium		
EQUILIBRIUM FOCUSED ON INTERVAL 1		
Strategy 1		
q1 (Prob. of commercial in interval 1 when this is strategy)	0.658 (0.010)	0.682 (0.009)
q2 (Prob. of commercial in interval 2 when strategy is 1)	0.254 (0.009)	0.200 (0.007)
Strategy 2		
q1	0.077 (0.008)	0.084 (0.007)
q2	0.668 (0.011)	0.684 (0.008)
Strategy NOT 1 OR 2		
q1	0.091 (0.005)	0.093 (0.005)
q2	0.021 (0.003)	0.021 (0.003)
EQUILIBRIUM FOCUSED ON INTERVAL 2		
Strategy 1		
q1	0.689 (0.007)	0.685 (0.009)
q2	0.072 (0.005)	0.047 (0.006)
Strategy 2		
q1	0.245 (0.007)	0.294 (0.007)
q2	0.668 (0.011)	0.620 (0.008)
Strategy NOT 1 OR 2		
q1	0.057 (0.004)	0.047 (0.004)
q2	0.055 (0.003)	0.082 (0.005)
Log Likelihood	-44267.3	-44970.3
Nash equilibria strategies	0.372,0.322	0.377,0.278
Number of market-weeks	1,673	1,673
Number of station-weeks	11,284	11,284
Test for Multiple Equilibria		
LRTS comparing this model with model with only one equilibrium	356.6	422.3
Bootstrapped LR test statistic distribution (499 replications, see Section 2.4)		
90th percentile	349.0	372.0
95th percentile	362.6	386.2
99th percentile	391.4	408.1

Notes
1. Standard errors computed using BHHH method in parentheses
2. Number of station-weeks is the number of station-weeks observations where a station has at least one commercial at some point in the hour at least one day during the week. A market-week observation has at least one home to market station with at least one commercial at some point during the hour at least one day during the week.
The number of station-weeks is higher than in Table 2.6 because I now include station-weeks with commercials during the hour at least one day during the week but never during intervals 1 or 2.

Chapter 3

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

3.1 Introduction

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

I use a new and very detailed panel dataset of airplay on music radio stations from 1998 to 2001 to provide new evidence on the effects of ownership. I find that common ownership of stations in the same metro-market and music category (hereafter I denote a metro-market

[1]The Competition in Radio and Concert Industries Act introduced to the Senate in January 2003 has the aim of creating "more diversity in radio programming" partly through tightening ownership restrictions (for example, on Local Marketing Agreements between stations). DiCola and Thomson (2002) argue that ownership concentration has harmed variety, a charge rejected by the National Association of Broadcasters (2002). Critics of ownership consolidation have criticised not only the effects of ownership concentration within local radio markets but also the effects of common ownership across different local markets: in particular, they have argued that this has led to homogenization of programming harming both listeners who want local radio and new musicians seeking airplay.

category by MMC) is associated with greater differentiation in station playlists. I find this result both when I look across metro-markets with different ownership structures and when I examine how changes in station ownership affect the location of particular stations. This variety-increasing effect is robust to different measures of station location and it is quite large in magnitude. For example, using a measure of station location that takes into account that some artists are alike and others are not, I find that when a pair of stations in an MMC become commonly owned they move at least 13% further apart. On the other hand, I find that common ownership of stations in different metro-markets results in, at most, a small homogenization of playlists.

The finding that a common owner increases the degree of differentiation between local competitors is consistent with a simple model in which only a common owner internalizes "business stealing" effects. If this is the primary effect of within-MMC common ownership then one would also expect common ownership to increase station listenership. I use panel data on station listenership to provide some evidence that when stations in an MMC become commonly owned they do indeed tend to increase their combined audience. However, the size of this effect is sensitive to the exact specification used and, in particular, to how the degree of substitution between categories is estimated.

Before describing the relationship between this paper and the existing literature on music variety, I define two terms which are used to classify a station's programming genre and which appear throughout the paper. The classification of stations which I use comes from BIAfn's *Media Access Pro* database which is also used by the FCC (e.g., FCC (2001a), (2001b)). A *format* is the narrowest available classification of the type of programming a station plays. An example of a music format is "Hot Adult Contemporary". A *category* (BIAfn calls this a format category, but I use category to be clear that it is different from a format) groups together formats with reasonably similar programming. Each format belongs to one category. Stations in the Adult Contemporary, Hot Adult Contemporary, Soft Adult Contemporary and Soft Rock formats are all classified in the Adult Contemporary category along with stations from 20 other formats. The number of formats in each category and the number of stations in the main formats within each category are listed in Table 3.1 for the seven music categories which are the focus of most of this paper. In some categories, such as Adult Contemporary or Rock, there are several formats containing a large number of stations whereas in other categories, such as Country, almost all of the stations are contained in a single format. In analyzing music variety I compare the playlists of stations which are in the same category but possibly different formats.

This is not the first paper to study the effect of radio mergers on variety. Berry and Waldfogel (2001) find that counts of the number of formats and the number of formats per station in each metro-market increased more, following the 1996 Telecommunications Act, in the largest metro-markets where the Act allowed more mergers. They interpret this result as providing evidence that within-market mergers increase variety. On the other hand, they also find that commonly owned stations within a market tend to be clustered in similar (although different) formats and they interpret this as suggesting that a common owner might limit variety increases in order to avoid leaving gaps in product space into which entry could occur. While my result that within-market mergers increase product differentiation is similar to Berry and Waldfogel's result, I use a quite different empirical method which reveals an important limitation in using station formats to measure variety. I use station-level playlist data to locate stations in product space. This shows that there can be considerable differences in the playlists of stations in the same format and that some stations in different formats can have quite similar playlists. I then use actual changes in station ownership (rather than the natural experiment of the 1996 Act) to examine how ownership affects the location of an individual station relative to other stations in its category. I find that within-MMC mergers increase variety but I also find that very little of this effect is reflected in changes in station formats.[2] This is not entirely surprising because a station's format is not assigned based on a rigorous analysis of what it plays but instead it is typically a label which the station assigns to itself.

Two previous studies have made use of limited quantities of playlist data. Williams et al. (2002), as part of the FCC's re-assessment of its ownership rules, use data on the top 10 most played songs on 174 stations in different formats in March 1996 and March 2001. They regress the change in a measure of distance between pairs of stations on a number of dummies

[2] I note that because I use a different format classification to Berry and Waldfogel it is possible that airplay changes would have been captured by format changes in their classification. However, this seems unlikely because the BIAfn classification which I use has a more detailed classification (more formats) than the Duncan *American Radio* classification which Berry and Waldfogel use.

including ones for whether the stations in the pair have the same owner and are in the same metro-market, are in the same format and in the same metro-market, and have the same owner and are in the same format. They find that variety increased within metro-market-formats over this time period but they find no clear relationship with station ownership. However, they do not look at the effect of common ownership on station pairs in the same or similar formats and the same metro-market i.e., at the three-way interaction between music type, metro-market and ownership. If common ownership primarily increases differentiation between metro-market competitors in the same or similar formats (i.e., within the same category) then it is this three-way interaction which should capture the effects of ownership. Using a much richer dataset to analyze station locations within categories, I show that within-MMC mergers can have quite large effects on variety. Chambers (2003) uses a one week cross-section of airplay data from March 2002 and finds that metro-markets with higher HHIs tend to play fewer song titles which are more than one year old. He interprets this as indicating that ownership consolidation reduces within-market diversity even though there is no relationship for other types of song title. In contrast, I find that within-MMC mergers increase variety using panel data and better measures of product differentiation.

The second part of the paper tests whether, consistent with the business stealing explanation for common ownership increasing within-MMC variety, stations which become commonly owned increase their combined listenership. Berry and Waldfogel (1999a) and Rogers and Woodbury (1996) provide evidence of business stealing in this industry prior to ownership liberalization using cross-sections of listenership data from different markets from the 1980s and early 1990s. In particular, these authors show that the total amount of radio listening and the amount of listening to individual formats is relatively insensitive to the number of stations in the market or in the format which suggests that additional stations primarily take listeners from existing stations. Borenstein (1986) also provides some weak evidence of business stealing among stations in the same format and in the same market using data on changes in listenership following station entry and exit in the largest 5 metro-markets from 1975-1984. In examining the effect of ownership changes, Berry and Waldfogel (1999b) find no systematic relationship between changes in total commercial radio listening in a market and the number of available formats following the 1996 Act. In contrast, I examine what happens to the audience of *individual stations* following ownership changes. I also show that the implied amount of business stealing within categories can be quite different if substitution patterns are estimated from within-market variation in the number of stations in each category rather than from cross-sectional variation across markets.

Section 3.2 reviews the main theories of product differentiation which are relevant to radio. Section 3.3 provides the empirical analysis of product differentiation and Section 3.4 the empirical analysis of listenership. Section 3.5 concludes.

3.2 The Theory of Product Differentiation in Radio

A small theoretical literature has examined the incentives for product differentiation in free-to-air advertiser-funded broadcasting.[3] Section 3.2.1 informally summarizes how the incentives for differentiation change when stations in an MMC are commonly owned rather than separately owned. Whether common ownership leads to greater differentiation depends on what is assumed about how the quantity of advertising is determined. Section 3.2.2 provides a simple model of music research in which stations in the same music category but different metro-markets tend to have more similar playlists under common ownership if listener tastes are correlated across markets. The footnotes contain some quotes from *Billboard* magazine which show that some of these effects are recognized within the industry.

3.2.1 Effect of Common Ownership of Stations in the Same Metro-Market Category (MMC) on Product Differentiation

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

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

Business Stealing Effect

Initially assume that c_A, c_B and p are fixed and that a's optimal location is a unique solution to first-order conditions. In this case, under separate ownership A's location satisfies (3.1) and under common ownership it satisfies (3.2)

$$\frac{\partial \pi_A}{\partial a} = pc_A \frac{\partial L_A(a, c_A, c_B)}{\partial a} = 0 \tag{3.1}$$

$$\frac{\partial(\pi_A + \pi_B)}{\partial a} = pc_A \frac{\partial L_A(a, c_A, c_B)}{\partial a} + pc_B \frac{\partial L_B(a, c_A, c_B)}{\partial a} = 0 \tag{3.2}$$

The difference is that under common ownership A takes into account how its location affects B's commercial audience, i.e., it internalizes "business stealing". Assuming that $\frac{\partial L_B(a,c_A,c_B)}{\partial a} > 0$, so that when the stations locate closer together B's audience falls, A locates further from B under common ownership.[4] If c_A equals c_B a common owner simply maximizes the stations' joint commercial audience, so this will also be higher under common ownership.

Of course, if A already has an existing location before a merger, a common owner will take into account any re-location costs, perhaps from alienating loyal listeners, in deciding how far to move A. In particular, if re-location costs are convex in the distance moved then a merger will result in a smaller increase in differentiation than if station locations could be chosen again costlessly.

Strategic Location Choice with Endogenous Quantities of Commercials

Now assume that p is fixed but that c_A and c_B are chosen in the second stage of a two-stage game. In the first stage A chooses its location a. Assuming that $\frac{\partial L_i(a,c_i,c_j)}{\partial c_i} < 0$ and $\frac{\partial L_i(a,c_i,c_j)}{\partial c_j} > 0$ (listeners dislike commercials), this resembles a standard game of price competition on a line in which producers choose locations before setting prices. Under separate ownership it is well known that A may strategically choose to locate far from B because this softens competition in setting advertising quantities in the second stage (Tirole (1988), p. 281-

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

282). A common owner, who sets c_A and c_B to maximize joint profits in the second stage, has no need to strategically differentiate the stations. The comparison of differentiation under different ownership structures now depends on the relative sizes of the business stealing and strategic differentiation incentives.

The internalization of business stealing tends to increase total commercial listenership as before but listenership may fall if the quantity of commercials increases under common ownership. On the other hand, if p is not fixed and a common owner reduces c_A and c_B in order to raise the price (p) of commercials then listenership will certainly increase under common ownership because the business stealing and advertising effects work in the same direction. This leads to the possibility that an observed increase in listenership following a merger of stations in the same metro-market may be primarily due to reduced advertising rather than increases in variety. In Section 3.4.3 I provide some evidence that, in fact, increased variety provides a better explanation for the increases in station listenership.

Entry Deterrence

As discussed by Berry and Waldfogel (2001), the possibility of future entry can also affect A's location decision. Suppose that once a has been chosen a potential entrant, independently owned and with some randomly drawn sunk costs of entry, chooses whether to enter between A and B. A now takes into account how its location decision will affect the profitability of entry.[5] Under common ownership, A considers how entry would reduce the revenues of both A and B whereas under separate ownership A only considers the effect on its own revenues. In addition, entry may cause a particularly large reduction in revenues when A and B are commonly owned if it creates fierce competition in the setting of commercial quantities. Therefore which ownership structure provides greater differentiation depends on the relative sizes of the entry deterrence, business stealing and strategic differentiation incentives.

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

3.2.2 Effect of Common Ownership of Stations in Different Metro-Markets on Product Differentiation

Effects such as business stealing only apply to stations which compete for the same set of listeners. However, many radio groups own stations in many different local radio metro-markets. I now present a simple model which explains how common ownership of similar stations in different metro-markets could lead to homogenization of these stations' playlists.[6]

Suppose now that A and B are in the same music category but different metro-markets and that each station is deciding which of two songs (S_1 and S_2) to add to its playlist. In each market one of the songs is a better match for local tastes and a station gets a benefit of Ψ ($\Psi > 0$), in the form of a larger audience, if it picks the better match for its market. Tastes are imperfectly correlated across markets so that if S_i is a better match in A's market then it is a better match in B's market with probability λ ($\lambda \geq \frac{1}{2}$) and vice-versa. Before it makes a decision about which song to add, each station can use a local market research technology to improve its information about listener tastes in its market. If a station does no research, it assigns a probability of $\frac{1}{2}$ to each song being the better match in its market. The research technology consists of the ability to do a succession of projects (indexed 1,2,3,...). Each project is successful with probability p in which case it reveals correctly the identity of the better match and otherwise it is unsuccessful and yields no information. Each successive research project costs more (so that there are declining returns to research expenditure) and a station sees the results of each project before deciding whether to do the next one, and obviously once the better match is identified research stops. Separately owned stations cannot share research results but commonly owned stations can do so costlessly.[7] In addition, a common owner can wait for the result of a research project on one station before ordering its other station to undertake additional research. Obviously a station with a research success chooses to play the better

[6] *Billboard* (Nov 16 2000) "At Infinity Radio - with more than 180 stations - regular conference calls are held, with programmers from similarly formatted stations discussing what music is working in their markets. This networking is intended to allow programers to maintain control, while enhancing the information upon which they base music decisions." Senior VP Programming at Clear Channel (quoted in same article) "Generally local PDs have complete authority with respect to music additions. They are encouraged to consult with their brand managers and share relevant research data as part of the decision process".

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

matched song. A common owner with a success on only one station will choose the same song on both stations if $\lambda > \frac{1}{2}$. A station with no information on which song is the better match is assumed to choose each song with equal probability whatever the ownership structure.

In this model it is straightforward to show that if $\lambda > \frac{1}{2}$, stations are more likely to choose the same song under common ownership.[8] For given research strategies on each station, the ability to share information under common ownership leads immediately to this result. However, common ownership also has two other effects which work in the same direction. First, a common owner has more incentive to do research on each station until one of the stations has a research success, because the first success yields benefits to both stations. Second, a common owner has less incentive to continue to do research to get a second success, which could lead to the stations choosing different songs, because, with $\lambda > \frac{1}{2}$, a second research success is likely to simply confirm the first research result (research redundancy).[9] Expected station payoffs are higher under common ownership because research information is used more efficiently. If $\lambda = \frac{1}{2}$ (tastes uncorrelated across markets) stations have the same research strategies and are equally likely to choose to add the same song under either ownership structure. In practice, it seems sensible to assume that there is some correlation in tastes across markets so, under the assumptions of this model, we would expect to see common ownership resulting in some playlist homogenization across markets.

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

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

3.3 Does Common Ownership Increase Music Variety?

In this section I use a panel of airplay data from music radio stations to analyze how station ownership and changes in station ownership affect product differentiation within a category. Section 3.3.1 describes the airplay data, Section 3.3.2 details three different measures of a station's location in product space, Section 3.3.3 outlines the regression specifications used, Section 3.3.4 provides summary statistics and Section 3.3.5 presents the results.

3.3.1 Airplay Data

Mediabase 24/7, a company which collects music radio airplay data for the music and radio industries, generously provided me with access to a sample of daily airplay logs from 1,095 contemporary music radio stations for the first week (Monday-Friday) of each month from April 1998 to December 2001. A daily log is simple a list of each song played with the name of the artist, the song title and the release year. I define a station's location in product space using the number of times each artist, or alternatively, each artist-song title combination was played. This ignores the role of non-music programming in affecting differentiation, but a station's choice of music is undoubtedly the most important aspect of a music station's product.[10]

The 1,095 stations are drawn from 7 categories and 148 Arbitron-defined metro-markets. The 7 categories are: Adult Contemporary (AC), Album Oriented Rock/Classic Rock (AOR), Contemporary Hit Radio/Top 40 (CHR), Country, Oldies, Rock and Urban.[11] A station's category in a given week is based on its format for the relevant (or nearest) Arbitron ratings period listed in BIAfn's *Media Access Pro* database together with BIAfn's Fall 2001 classification of formats into categories. The database also lists each station's home metro-market, as designated by Arbitron in Fall 2001. Every rated station has a home metro-market based on either its city of license or the market in which it attracts most of its listeners. The airplay sample does not include all stations in these 7 categories in the 148 metro-markets. However,

[10]I note three features of how artists or artist-song title combinations are defined: recordings of the same song by different artists are treated as different artist-song title combinations; a singer is treated as a separate artist when recording as an individual or as part of a group; and, Mediabase groups some different songs together under the title "Christmas Music" with artist as "Various". I treat these as a single artist-song title combination but the results are completely unaffected if I drop all December observations.

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

because Mediabase is primarily interested in stations with large audiences, the stations in the sample do account for the vast majority of listening in their MMCs, as shown in Table 3.2. Coverage is particularly good in the larger metro-markets. The categories with the most stations in the airplay sample are AC and CHR. There are relatively few Oldies stations in the sample, especially in smaller markets.

The airplay panel is unbalanced in several dimensions. Mediabase has tracked more stations and metro-markets over time, and some stations exit the sample during 2001 primarily due to changing to different categories. For some weeks I do not have 5 days of data: in particular, I have only 1 day of data for any station in 11 weeks in 1998 and 1999 (10 of them in 1999), 4 days for 3 weeks and a full 5 days for 31 weeks (including all but 1 week in 2000 and 2001). A large number of individual station days are also missing for reasons that should not be correlated with airplay. Table 3.3 provides some summary statistics on the structure of the panel. Overall, there are 35,750 station-weeks of airplay data. Two robustness checks in Section 3.3.5 show that the unbalanced nature of the panel does not drive the results.

3.3.2 Measures of Station Location

I now explain how I use the airplay data to locate stations in product space. Station program directors only update playlists every week or so, so I aggregate the daily logs to give weekly station playlists. If a station has one or more days of data missing then its weekly playlist is based only on the remaining days. I examine the relative location of stations *in the same category* and do not consider the relative locations of stations in different categories. The assumption is that stations in different categories do play different kinds of music and that a station's choice of exactly which music to play is primarily affected by the choices of stations playing similar kinds of music, i.e., those in the same category.

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

Measure 1: each artist is a separate dimension of product space. Every artist played by any station in the category during the week defines a separate and orthogonal dimension of the product space. A station's location is defined by each artist's share of its playlist. For example, suppose that there are only three artists (X, Y and Z) and that station i plays X 10 times, Y not at all and Z 5 times. i's (X,Y,Z) location is $(\frac{2}{3}, 0, \frac{1}{3})$. In reality a station in the sample plays, on average, over 177 different artists during a 5 day week and the stations in a category together play over 1,200 different artists. The distance between two stations is defined as the angle (in radians) between their location vectors.[12] The distance between two stations with no artists in common will therefore be $\frac{\pi}{2}$.

Measure 2: each artist-song title combination is a separate dimension of product space. A station's location is defined in the same way as for Measure 1, except that I use data on artist-song title combinations rather than just artists. A station plays, on average, over 395 different artist-song title combinations during a 5 day week.

Measure 3: location in a 2-dimensional plane allowing some artists to be more similar than others. Stations are located using a 2-step procedure. In the first step, the artists played in a category-week are located in a 2-dimensional plane.[13] As I do not have data on artist characteristics, such as age or group size, I assume that artists played heavily by the same stations are more similar (closer together in product space) than those played heavily by different stations. For example, the correlation coefficient between the number of plays of Elton John and plays of Phil Collins on Adult Contemporary (AC) category stations in the first

[12]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. An alternative interpretation of the distance is available. Suppose that each station's location in artist space is projected onto the unit hypersphere with number of dimensions equal to the number of artists. The distance between the stations is equal to the the shortest distance between the two stations along the surface of the hypersphere.

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

week of November 2001 was 0.8214. The correlation between Elton John and U2 was -0.6631. I first locate each artist in a high-dimensional station space in a similar way to the location of stations in Measure 1 but now each station defines a separate and orthogonal dimension of the product space and an artist's location vector is given by the share of its plays coming from each station. I then calculate the distance between each pair of artists as the angle (in radians) between their location vectors. I then project each artist into a 2-dimensional plane, choosing their locations to minimize the sum of squared differences between the distance between a pair of artists in the plane and the distance between the pair in the high-dimensional station space, i.e., I want to minimize

$$\sum_{i=1}^{A-1} \sum_{j=i+1}^{A} \left(d_{ij} - \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \right)^2 \tag{3.3}$$

where (x_i, y_i) are the coordinates of artist i in the plane, A is the number of different artists played by any station in the category-week and d_{ij} is the distance between artists i and j in the high-dimensional station space. This is a Non-Linear Least Squares problem in which the xs and ys are parameters to be estimated. As pair distances only measure relative locations, I fix the most played artist in the category-week at the origin and fix the second most played artist on the x-axis. The axes themselves have no interpretation.

Unfortunately it is not feasible to locate all of the artists played in a category-week simultaneously because 1,200 artists would give 2,397 parameters. I reduce the problem slightly by dropping all artists who have less than 10 plays by all stations in the category. Appendix A describes the exact procedure used to locate the remaining artists: it involves first locating the 30 most played artists (who account, on average, for over 42% of plays) and then sequentially locating the remaining artists.

The best evidence that this procedure works is that it produces a highly plausible pattern of artist locations. Figure 3-1 shows the locations in the plane of the 30 most played artists on AC category stations in the first week of November 2001. Elton John (the most played artist) is at the origin and the Backstreet Boys are on the x-axis. The maximum distance between artists in the high-dimensional space is 1.5708 so artists who are roughly this distance apart in the plane (such as Rod Stewart and the Dave Matthews Band) are rarely played together.

Figure 3-1: 30 Most Played Artists on Stations in the Adult Contemporary Category in the First Week of November 2001 Located in 2-Dimensional Music Product Space

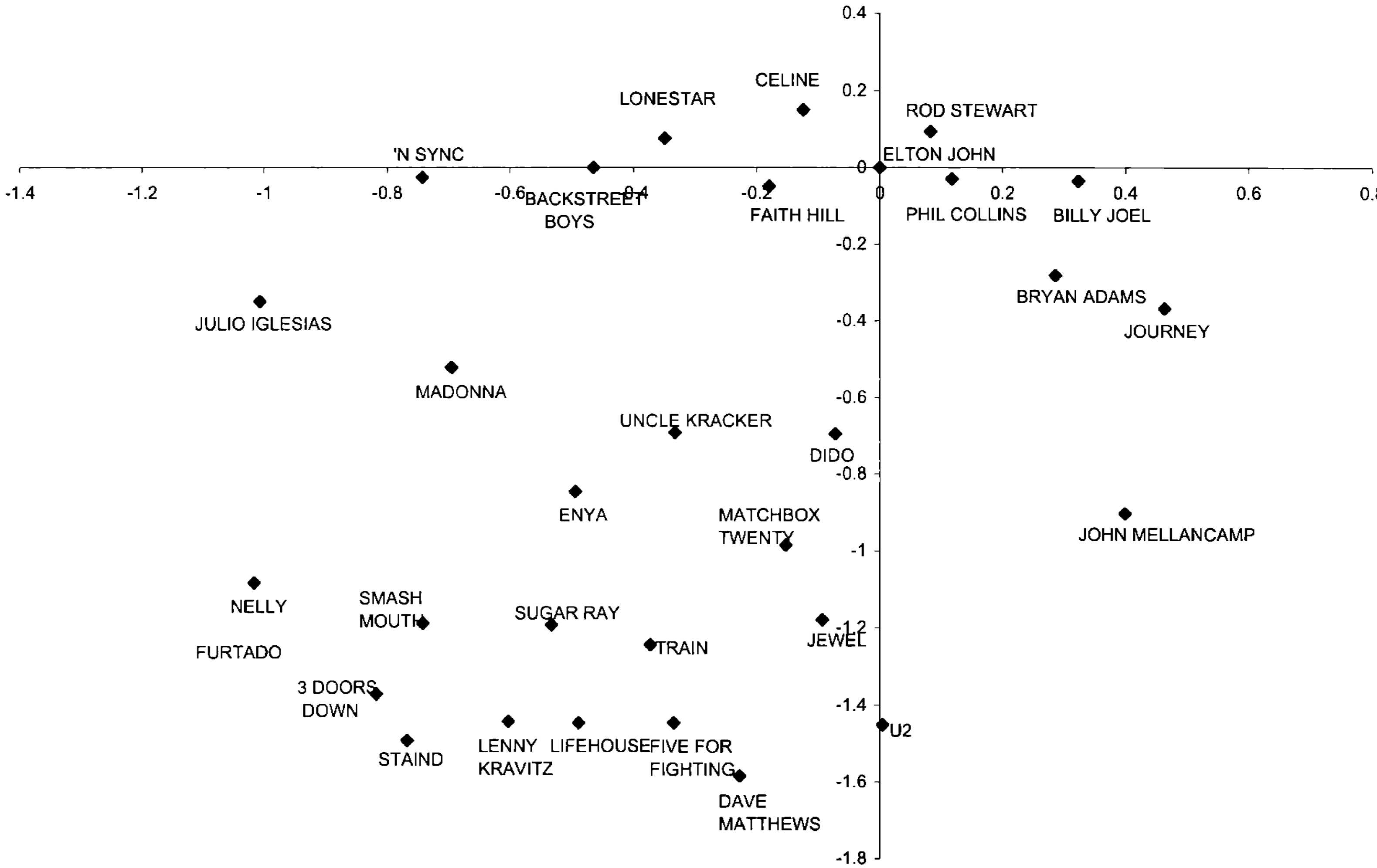
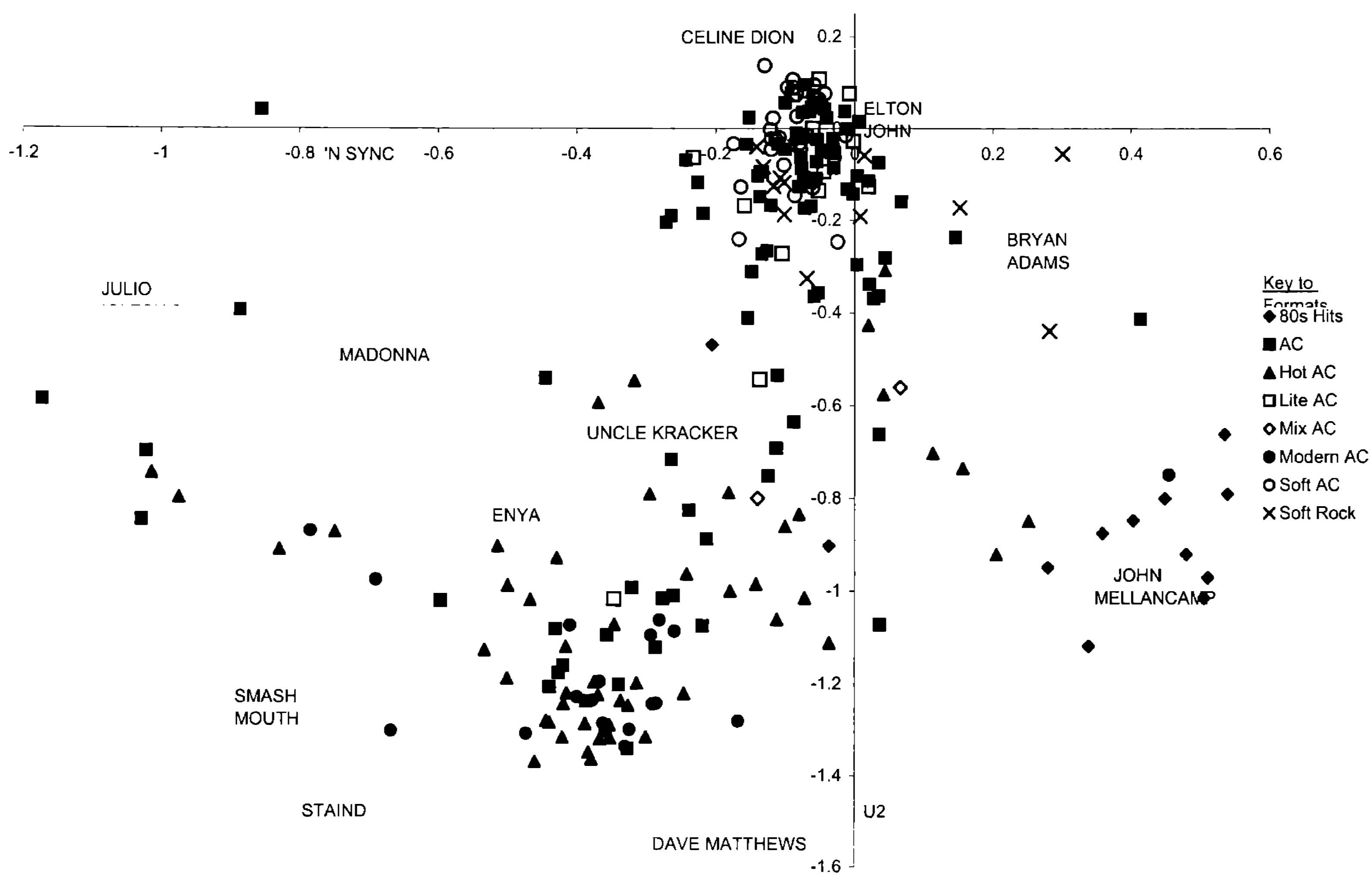


Figure 3-2: Stations in the Adult Contemporary Category Located in 2-Dimensional Music Product Space, based on Artist Playlists in the First Week of November 2001 plus Selected Artist Locations



As expected, Elton John and Phil Collins are located close to each other and to artists such as Rod Stewart and Billy Joel. In contrast, U2 is located much closer to artists such as the Dave Matthews Band and Jewel.

In the second step, each station is located in the plane at the weighted average of the coordinates of the artists with the weights corresponding to the share of each artist in its playlist. Continuing the Measure 1 example, if artist X was located at (0,0), Y at (1,0) and Z at $(-\frac{1}{3}, \frac{1}{2})$ station i would be located at $\left((\frac{2}{3} \times 0) + (0 \times 1) + (\frac{1}{3} \times -\frac{1}{3}), (\frac{2}{3} \times 0) + (0 \times 0) + (\frac{1}{3} \times \frac{1}{2})\right) = (-\frac{1}{9}, \frac{1}{6})$. 5 station-week playlists which do not contain any artist played at least 10 times in the category-week are dropped. The straight line distance between a station and any point in the plane can be calculated easily.

Figure 3-2 shows the implied locations of AC stations in the first week of November 2001 together with some of the artists from Figure 3-1. I give stations in different formats within the AC category different symbols to provide an illustration of how well formats reflect differences in the kind of music stations actually play.[14] As one would expect, Soft AC, Lite AC and Soft Rock stations are clustered near Elton John and Celine Dion whereas the Hot AC and Modern AC stations are located closer to U2, the Dave Matthews Band and Smash Mouth. Stations in the same format do tend to play more similar music than stations in different formats. However, there is considerable heterogeneity in the locations of stations in some formats, such as Adult Contemporary, and stations in some different formats such as Lite AC, Soft AC and Soft Rock tend to be located very close together suggesting that there are only slight differences between these formats.[15] This suggests that while counting the number of formats available

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

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

in a market, as Berry and Waldfogel (2001) do, should provide some information on changes in variety, individual station airplay data should allow a more precise analysis.

3.3.3 Regression Specifications

I now describe three different regression specifications to examine the effects of station ownership on station location and differentiation.

Distances between station pairs

The dependent variable is the distance between each pair of stations in the same category each week. The linear specification is

$$y_{ijw}^{PAIR} = X_{ijw}\beta_1 + C_{ijw}\beta_2 + W_w\beta_3 + \varepsilon_{ijw} \quad (3.4)$$

where y_{ijw} is the distance between stations i and j in week w, C_{ijw} are dummy variables for the music category of the pair, W_w are dummy variables for the different weeks and ε_{ijw} is an error term which I will discuss shortly. Given these dummies and the various X variables I describe in a moment, the coefficients on the X variables reflect how much further apart, on average, a pair of stations with the X characteristics are than a randomly drawn pair of separately owned stations from different geographic regions but the same music category, controlling for any average week effects. The X matrix contains the following dummy variables:

$SAME\_REGION$: takes value 1 if i and j are home to metro-markets in the same one of BIAfn's 9 geographic regions. This allows regional differences in music tastes to lead to stations in the same region playing similar music.

$SAME\_MARKET$: takes value 1 if i and j are home to the same metro-market. Given the other dummies, the coefficient reflects whether separately owned stations in the same metro-market tend to locate further apart than a randomly drawn pair of separately owned stations from the same region.

$SAME\_OWNER$: takes value 1 if i and j have the same owner in week w. I find a station's owner using BIAfn's transaction history for each station.[16] The coefficient shows how

[16]In cases where a single radio group owns several different firms which own radio stations I define ownership at

much further apart, on average, commonly owned stations in different metro-markets are than a randomly drawn pair of separately owned stations in different metro-markets.

SAME_MKTOWNER: takes value 1 if i and j are home to the same metro-market and have the same owner. The sum of the *SAME_OWNER* coefficient and the coefficient on this dummy reflect whether commonly owned stations in an MMC tend to locate further apart than separately owned stations in the same MMC.

I estimate (4.9) with and without dummies, or fixed effects, for the pair of stations interacted with the music category (hereafter, category-pair dummies).[17] With fixed effects, the ownership coefficients are identified by how much the distance between a category-pair changes when the stations change whether they are commonly owned. To understand why the results with fixed effects may be different, suppose that I find, without fixed effects, that stations with the same owner in different metro-markets have very similar playlists. This could be either because group owners homogenize playlists or because a group buys stations which play very similar music to exploit economies of scope in research without making significant changes to the type of music played on any station. If the second explanation is correct, I expect the *SAME_OWNER* coefficient to be zero in the fixed effects specification.

Testing the significance of the coefficients is complicated by the fact that the ε_{ijw} residuals may not be independent across pair-weeks. There are two different problems. First, because stations tend to stay in similar positions from month to month, the residuals for a given pair of stations will be correlated across weeks. This is a relatively standard problem which can be dealt with by, for example, clustering the standard errors at the level of the category-pair. Second, the residuals of different pairs may be correlated because each station's location affects the pair distance between it and any other station in its category so that, for example, ε_{ijw} will be correlated with ε_{ikw} and ε_{jlw}. If each pair distance is treated as independent then the significance of the results may be overstated.[18] This is a non-standard problem. As I only calculate the pair distances between stations within a music category, I calculate standard

the group level. One problem is that for all but a station's most recent transaction BIAfn lists the announcement date of the deal rather than the date on which the transaction was completed. However, the results are not sensitive to assuming that such deals were completed several months after the date listed in the BIAfn database.

[17]This means that a pair gets a new fixed effect if both stations change categories to the same new category, although this is rare.

[18]An alternative way of seeing the problem is that there are many more pair distances than station locations (e.g., 100 locations give 4,950 pair distances).

errors which are clustered at the level of the category. There are seven music categories in the data and, to calculate p-values, I assume that the t-statistic has a t distribution with 6 degrees of freedom (the number of clusters/categories minus 1).[19] Donald and Lang (2001) and Wooldridge (2003), in the context of a different model to the one considered here, discuss the complications which can arise when the number of clusters is small so in Appendix B I provide the results of simulation exercises which confirm that the resulting p-values are approximately correct. A robustness check, reported in Section 3.3.5, which drops the vast majority of the data so that each station's location only enters one category-pair distance, gives similar results.

Alternative Specifications: Metro-Market Category Average Distances and the Distance of Each Station from the Centre of its Category

I also estimate two alternative specifications to check that the main result, that common ownership of stations in an MMC increases differentiation, is not simply a consequence of the pair distance specification. Additionally, these alternative specifications do not suffer from non-standard problems in determining the appropriate standard errors.

MMC Average Distances The dependent variable is the average of the pair distances between stations in an MMC-week. MMC-weeks with only one observed station are dropped and distances between stations which are home to different metro-markets are not used at all. The linear specification is

$$y_{mw}^{MMC} = X_{mw}\beta_1 + W_w\beta_2 + D_{mw}\beta_3 + \varepsilon_{mw} \tag{3.5}$$

X_{mw} is a variable reflecting the degree of common ownership of the stations in MMC m. Alternative X_{mw}s are the average of the $SAME\_MKTOWNER$ ($MEAN\_SAME\_MKTOWNER$) dummies for the different pairs in the MMC and a dummy which takes value 1 if any of the stations are commonly owned ($ANY\_SAME\_MKTOWNER$). W_w are week dummies. D_{mw} includes controls such as dummies for the number of airplay stations in the MMC interacted with category dummies. The coefficient on the ownership variable reflects whether stations

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

tend to be spaced further apart in MMCs where stations are commonly owned than in those in which stations are not commonly owned. I estimate (3.5) both with and without fixed effects for the identity of the stations used in calculating the MMC-week average.[20] Each station-week playlist contributes to only one observation on the dependent variable so I assume that ε_{mw} is independent across MMCs in a given week. However, I cluster the standard errors so that ε_{mw} may be correlated across observations from the same MMC in different weeks.

Distance of Each Station from the Centre of its Category I also investigate whether common ownership in an MMC results in a station specializing more within its category. Suppose two separately owned, symmetric stations locate on the unit interval with a uniform distribution of listeners. It is natural to assume that in equilibrium they will be located symmetrically around $\frac{1}{2}$. If they become commonly owned and they move apart to internalize business stealing we would expect the stations to move further away from $\frac{1}{2}$ as well as from each other. The pair distance specification tests whether commonly owned stations locate further from each other and this specification tests whether they locate further from the centre of the category.[21]

The dependent variable is the distance between each station and the centre or average location in the category-week. For Measures 1 and 2, the centre is defined by the aggregating the weekly playlists of all of the stations in the category and the distance between a station and the centre is given by the angle between the station location vector and the vector for this aggregate playlist. For Measure 3, the centre is the average location of the stations in the category (averaging the station x– and y-coordinates) and the each station's distance is measured by the straight line distance in the plane from the station to this point. The linear regression specification is:

$$y_{iw}^{CENTRE} = X_{iw}\beta_1 + C_{iw}\beta_2 + W_w\beta_3 + \varepsilon_{iw} \tag{3.6}$$

[20]For example, suppose I have airplay data for stations A and B in MMC m for weeks 1-20 and data on A, B and C for weeks 21-45. In this case, I would include a one fixed effect for MMC m for weeks 1-20 and a different fixed effect for weeks 21-45.

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

X_{iw} contains a dummy for whether there are other stations home to i's MMC ($ANOTHER\_STATION$) and the number of stations i's owner has in the MMC ($NUMBER\_OWNED\_IN\_MMC$). These variables are calculated to include stations which are not in the airplay sample as well as those which are. C_{iw} and W_w are category and week dummies. I estimate (3.6) with and without station fixed effects. Assuming that each station's playlist has a negligible effect on the centre of category, each station-week playlist contributes to only one observation on the dependent variable so ε_{iw} is assumed to be independent across stations. I cluster the standard errors so that ε_{iw} may be correlated across observations on the same station in different weeks.

3.3.4 Summary Statistics

The first part of Table 3.4(a) presents summary statistics on the pair distance measures by category. Country stations are closer together, on average, than stations in other categories which is consistent with almost all Country stations belonging to the same Country format (Table 3.1). Some pairs of stations in each category have no playlist overlap at all so the Measure 1 and 2 distances for these pairs are $\frac{\pi}{2}$.[22] Measure 3 places some station pairs in each category very close together even though Measures 1 and 2 indicate that no pairs have very close to identical playlists. This is because if stations play similar, but not identical, artists Measure 3 can place them close together but the other measures do not. The next section of Table 3.4(a) provides summary statistics for pairs which are in the same format as well as the same category (as explained in footnote 14 I define 34 formats for this purpose). Pairs in the same format are closer together than pairs which are just in the same category but, consistent with the pattern for AC category stations in Figure 3-2, there is clearly considerable playlist heterogeneity within some formats.

As a comparison, I also calculated the Measure 1 and 2 distances between pairs of stations in *different* categories for November 2001 (I did not do this exercise for Measure 3 because it would involve locating a very large number of artists). As expected, these average distances, (Measure 1 1.484 and Measure 2 1.515) are significantly higher than the averages for pairs in the same category. Figure 3-3 illustrates the same point, showing the projection of all stations rated in

[22]The regression results for these measures are robust to using a number of methods to adjust for censoring of the dependent variable.

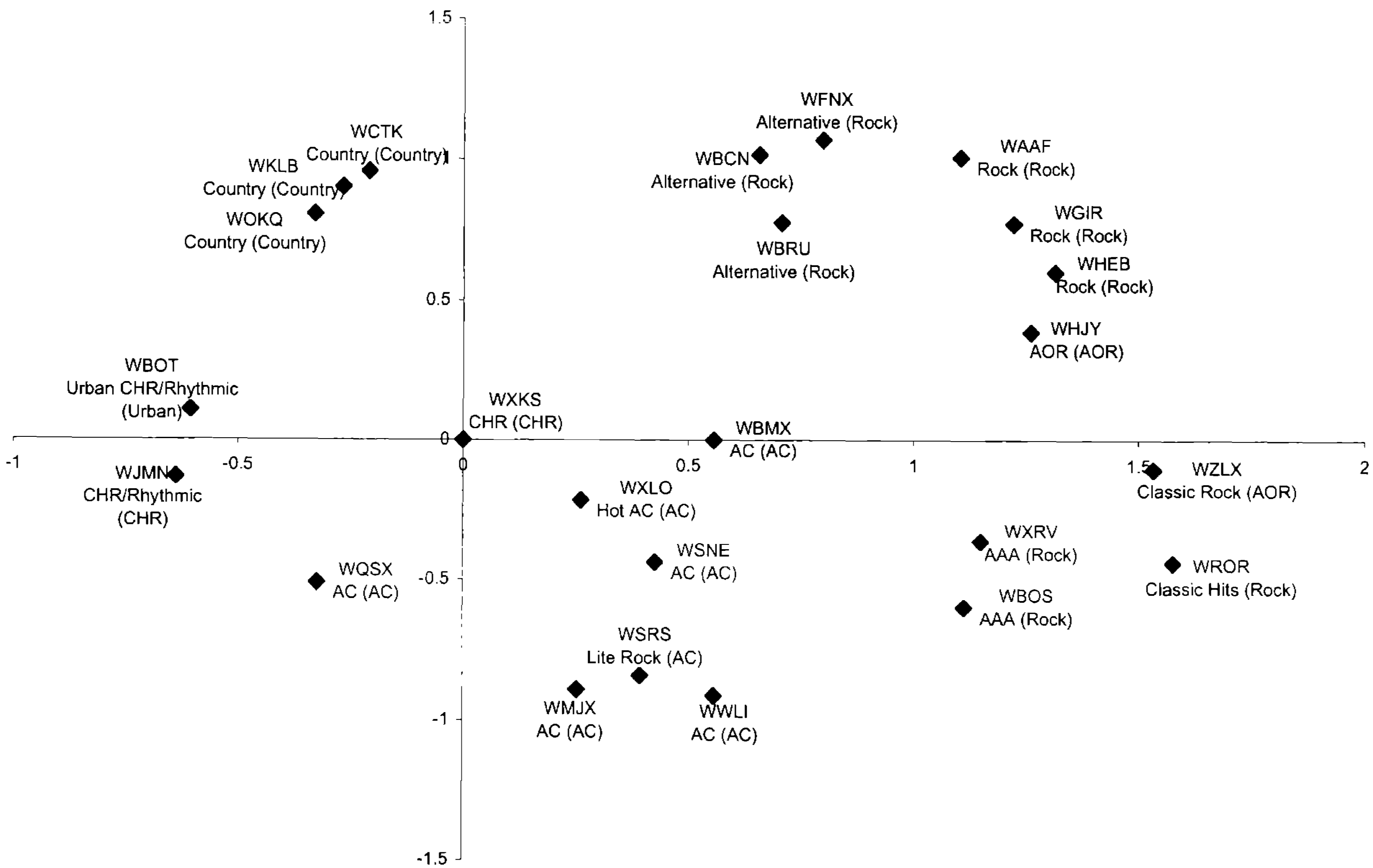
Boston in November 2001 based on their Measure 1 distances.[23] Stations in the same category are typically clustered together, although stations in the Album Oriented Rock/Classic Rock (AOR) and Rock categories are not clearly separated. The location of individual stations also makes sense: for example, the CHR/Rhythmic WJMN is close to the Urban CHR/Rhythmic WBOT.

Table 3.4(a) also provides summary statistics for the distance measures used in the other specifications. The MMC average distance is significantly greater than the average distance between pairs of stations in the top part of the table. This previews my regression result that stations in the same MMC tend to differentiate themselves to some extent whatever the ownership structure.

Table 3.4(b) provides summary statistics for the explanatory variables. There are 109,175 distinct category-pairs of stations (with an average of 23 observations per pair). 688 distinct pairs are home to the same MMC and 154 of these pairs are commonly owned at some point during the sample. These 154 pairs identify the $SAME\_MKTOWNER$ coefficient when category-pair fixed effects are not included. These pairs are spread across all the categories apart from Oldies. There are 46 changes affecting whether these pairs are commonly owned during the sample, affecting 40 distinct pairs. These changes identify the $SAME\_MKTOWNER$ coefficient when category-pair fixed effects are included. The number of pairs which identify the $SAME\_MARKET$ and $SAME\_MKTOWNER$ coefficients is small and an impressive feature of the results is that the coefficients on these dummies are significant and very robust. 12,846 distinct pairs from different metro-markets are commonly owned at some point (this includes some Oldies pairs) and there are 7,385 changes in common ownership for these pairs. These pairs identify the $SAME\_OWNER$ coefficient. The very large number of pairs for which all of the dummies are zero simply act as controls (as reflected in the coefficients on the category and week dummies) against which the effects of the variables of interest are measured. The averages of the $SAME\_MKTOWNER$ variables for the MMC average distance specification are larger than for the pair distance specification because observations from pairs in different markets are not used. The average values of $NUMBER\_OWNED\_IN\_MMC$ and

[23]The projection procedure is similar to that used to project artists for Measure 3. WXKS is fixed at the origin and WBMX on the x-axis. The figure includes stations which are not home to Boston but which were rated in Boston as well as their home market.

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



$ANOTHER\_IN\_MMC$ (used in the distance from the centre of the category analysis) reflect the fact that these variables are calculated to include stations which are not in the airplay sample.

3.3.5 Variety Results

Pair Distance Results: No Category-Pair Dummies

Table 3.5 presents the results from the pair distance regressions without category-pair dummies. Columns (1)-(3) report the results of the most basic specification using location Measures 1, 2 and 3 respectively. The pattern of the coefficients is very similar across these columns. However, it is noticeable that most of the coefficients of interest are larger relative to the average distance between pairs of stations (Table 3.4) for Measure 1 and especially Measure 3. One interpretation of this is that Measure 3 (which takes into account the similarity of different artists) does a better job of capturing the most important aspects of product differentiation.

The $SAME\_REGION$ coefficient indicates that stations in the same region tend to play more of the same artists and song-titles than those in different regions, which is consistent with some regional variation in tastes for particular artists and songs. The $SAME\_MARKET$ coefficient shows that, on average, separately owned stations in the same MMC are significantly more differentiated than stations drawn randomly from different metro-markets. Even if separately owned local competitors do not internalize business stealing, they do not locate very close together and instead they appear to have some incentive to strategically differentiate. The effect is quite large. The average Measure 1 distance between two randomly drawn Adult Contemporary (AC) category stations is 1.078, so the coefficient, net of the region effect, indicates that two AC stations in the same MMC are, on average, 11% further apart than a randomly drawn pair. The Measure 3 coefficient indicates that they are 27% further apart. The $SAME\_OWNER$ coefficients are negative indicating that pairs of stations from different metro-markets tend to be closer together if they are commonly owned. This is consistent with the model in Section 3.2.2 which showed how the sharing of music research would lead commonly owned stations to have more similar playlists. However, the coefficients are only weakly significant and are rather small implying that two randomly drawn AC stations are, on average, 4% closer together if they are commonly owned under Measure 1 and 6% under Measure 3. One interpretation is that the correlation of tastes across markets is relatively weak. The $SAME\_MKTOWNER$ coefficient shows that, on average, stations in the same MMC tend to locate further apart when they are commonly owned (the sum of the $SAME\_OWNER$ and $SAME\_MKTOWNER$ coefficients is significant at the 1% level for Measures 1 and 3 and at the 5% level for Measure 2). Thus even though separately owned stations appear to have some incentive to strategically differentiate, common ownership leads to even more differentiation, consistent with the main effect of common ownership being the internalization of business stealing. This result is also consistent with Berry and Waldfogel (2001)'s result that common ownership leads to more variety. The implied increase in differentiation is quite large. Based on Measure 1 and the average AC pair distances, a commonly owned pair from the same MMC is, on average, 23% further apart than a randomly drawn pair and 10% further apart than a separately owned pair from the same MMC. The Measure 3 increases are 55% and 22% respectively.

If commonly owned stations in an MMC differentiate themselves from each other to internalize business stealing, it is natural to ask whether they move closer to other stations in the MMC in order to steal more business from them. To investigate this I define a dummy ($ONE\_MKTOWNER$) which is 1 for separately owned pairs in the same MMC where one or both of the stations in the pair is commonly owned with another station in the MMC (whether or not that station is in the airplay sample). $ONE\_MKTOWNER$ is 1 at some point during the sample for 296 distinct pairs. If commonly owned stations do move closer to other stations then the coefficient should be negative. Instead, in columns (4)-(6), the coefficients are small, statistically insignificant and vary in sign. Commonly owned stations in the same MMC locate further from each other on average, but not closer to other stations.

Another obvious question is whether the $SAME\_MARKET$ and $SAME\_MKTOWNER$ coefficients simply reflect the fact that stations in an MMC, and particularly those stations which are commonly owned, tend to be in different formats. If this is the case, the increase in variety could be captured just as well by using counts of the available formats together with some information on how different, on average, particular formats are from each other. To investigate this, I include dummies for the formats of the pair (e.g., a Hot AC-Soft Rock dummy which is 1 if one of the stations is Hot AC and the other is Soft Rock). If the previous results do simply reflect different station formats then the coefficients on the variables of interest are now expected to be zero. I also include the variables of interest interacted with a dummy for whether the stations are in the same format in order to test whether the effects of ownership are more pronounced for stations in the same format. For example, if the sharing of music research across commonly owned stations leads to more homogenization then the effects may be stronger at the format level than the category level because stations in the same format are more likely to be considering adding the same songs to their playlists. The results are given in columns (7)-(9). The sums of the coefficients on the main variables and the interactions are of roughly the same magnitude as the coefficients in columns (1)-(3) showing that the previous results do not simply reflect different station formats because stations in the same format can have quite different playlists. Common ownership of stations in different MMCs seems only to lead to homogenization when the stations are in the same format. The homogenization is also more pronounced when stations are located using Measure 2 which is consistent with the music research model because research assesses whether particular songs, rather than particular artists or types of music, should be added to playlists. The $SAME\_MARKET$ and $SAME\_MKTOWNER$ coefficients and their interactions show that while the variety-increasing effects of within market ownership are larger for stations in the same format, there are also significant effects for stations which are in the same category but different formats.

In columns (10)-(12) I restrict the sample to pairs which are in the same region, following the suggestion of a radio executive, that, because radio groups share research primarily at the regional level, homogenization across markets due to common ownership would be more marked for pairs in the same region. In addition, restricting the sample allows me to cluster the standard errors at the category-region level giving a much larger number of independent clusters (61) than before. There are 1,875 different category pairs in the same which are ever commonly owned. However, while the $SAME\_OWNER$ coefficients are larger, than in columns (1)-(3), the differences are not significant.

Pair Distance Results: Category-Pair Fixed Effects

Table 3.6 gives the results when category-pair dummies are included. The ownership coefficients are identified from changes in the distance between pairs which change whether they are commonly owned. Stations do not change their geographic locations so the $SAME\_REGION$ and $SAME\_MARKET$ coefficients cannot be identified. As described below the table, these regressions use a large sub-sample of the actual data to allow the additional dummies to be included. The results are not sensitive to the selection or the size of the sub-sample.

The coefficients in columns (1)-(3) are smaller in absolute magnitude than the corresponding coefficients in Table 3.5. The $SAME\_OWNER$ coefficients fall by more proportionately and are not significant at the 10% level despite the large number of changes in whether the stations are commonly owned. The Measure 1 coefficient implies that a pair of AC category stations in different metro-markets switching from separate to common ownership become only 1% closer together on average (Measure 3 2%). The sum of the $SAME\_OWNER$ and $SAME\_MKTOWNER$ coefficients is significant at the 2% level for Measures 1 and 3, but it is not significant at the 10% level for Measure 2. The implied increase in differentiation is still relatively large in magnitude: the Measure 1 coefficients imply that a pair of stations in an MMC move 7% further apart, on average, when they become commonly owned (Measure 3 13%). This compares with an estimate of 10% (Measure 3 22%) from the regressions without category-pair dummies. This fall in magnitude may be explained by costs, for example from alienating loyal listeners, which prevent stations from quickly changing their playlists following ownership changes. Another interpretation for the change in the $SAME\_OWNER$ coefficient is that a radio group may buy stations in different metro-markets which already play quite similar music in order to exploit economies of scale and scope in research.

To illustrate the size of the $SAME\_MKTOWNER$ effect (net of the $SAME\_OWNER$ effect) Table 3.7 presents hypothetical changes to two actual playlists from November 2001. WBMX-FM and WMJX-FM are both Boston Adult Contemporary stations. The stations are both in the Adult Contemporary format as well as the AC category, but their playlists show that they focus on quite different artists. The first part of the table shows how many times each station played 15 of the artists from Figure 3-1. WMJX played artists like Elton John and Faith Hill heavily, while WBMX focused on artists such as U2 and the Dave Matthews Band. Their playlists overlap for artists in the middle of Figure 3-1 like Matchbox Twenty, Enya and Dido. The second part of the table shows playlist changes which would move the stations further apart by almost exactly the same amount implied by the Measure 1 $SAME\_MKTOWNER$ coefficient (net of $SAME\_OWNER$), with each station playing less of the Enya-type artists and more of its specialist artists keeping the total number of plays on each station the same. The implied playlist changes are clearly non-trivial. The change in the Measure 3 distance is only slightly more than one-half of the change implied by the Measure 3 coefficients, even though these playlist changes were consciously designed to draw stations further apart in Measure 3 product space. The changes to playlists implied by the Measure 3 coefficients are therefore even larger.

Columns (4)-(6) show that when stations in an MMC become commonly owned they do not move closer to stations in the MMC owned by other firms: the $ONE\_MKTOWNER$ coefficients are all small, insignificant and vary in sign. This was also the pattern without fixed effects. Columns (7)-(9) includes format pair dummies and interactions of the ownership variables with the $SAME\_FORMAT$ dummy. The sums of the coefficients on the main effects and interactions are broadly similar to columns (1)-(3) showing that the implied playlist changes are not simply a reflection of changes in station formats. The $SAME\_MKTOWNER$ effect is not larger for stations in the same format than for stations in the same category: however, as there are only 3 such pairs which change whether they are commonly owned and are home to the same MMC this is not surprising. As before, the homogenization effect of common ownership of stations in different markets, is estimated to be larger and more statistically significant when the stations are in the same format and stations are located using Measure 2. However, even with this measure, the homogenization effect is less than the variety-increasing effect of within-MMC common ownership. Columns (10)-(12) restricts the sample to distance between stations in the same region. The $SAME\_OWNER$ coefficients are little unchanged showing that common ownership does not lead to pronounced homogenization even within regions. In addition because the standard errors are clustered at the category-region level , because I do not include distances between pairs of stations from different regions, the significance of the results increases. In particular, the variety-increasing effect of within-MMC common ownership is significant, even with Measure 2, at the 5% level.

Pair Distance Results: Robustness Checks

Table 3.8 presents the results of eight robustness checks on the Measure 1 and Measure 3 regressions in columns (1) and (3) of Table 3.5 and 3.6. The results are similar for Measure 2 but I do not report them to save space.

Some stations have short weekly playlists (for example, because they have a high proportion of talk programming) and I do not have a complete set of daily logs for some station-weeks. To make sure that these observations do not have a significant impact on the results, check 1 drops pair-weeks in which either stations has one or more daily logs missing and check 2 drops pair-weeks in which either station has less than 1,000 plays (this also drops all of the observations from those weeks where all stations have only one day of data). The coefficients remain almost exactly unchanged.

Check 3 treats a pair as being in the same metro-market if there is any metro-market in which both stations are rated. For example, WBMX-FM is home to Boston but is also rated by Arbitron in Providence while WSNE-FM is home to Providence but is also rated in Boston. I now set $SAME\_MARKET$ equal to 1 for an additional 155 distinct category-pairs like this. 13 of these pairs are also commonly owned at some point during the sample (so $SAME\_MKTOWNER$ is now 1 when they are commonly owned) and, in fact, all of these pairs change whether they are commonly owned during the sample. The $SAME\_MARKET$ and $SAME\_MKTOWNER$ coefficients fall and, with fixed effects, $SAME\_MKTOWNER$ becomes insignificant. This suggests that stations' location decisions are only affected by considerations in their home metro-market. This is not surprising because, on average, 81% of the audience of a station rated in more than one metro-market comes from the station's home market as does 68% of the audience of a station rated in at least 5 markets.[24]

Check 4 investigates whether Williams et al.'s (2002) finding that "diversity has grown significantly among stations within the same format and within the same city [but] the role that [ownership] concentration plays appears to be less clear" explains my results. If all stations

[24]Author's calculation based on Arbitron Average Quarter Hour Persons listening data for Fall 2001 for the stations in the airplay data. The averages for all stations are very similar (79% and 70.3% respectively) and the proportions are even higher based on the number of different people who listen to a station for at least five minutes during a broadcast week (Cume Persons). Stations will also care more about increasing their home metro-market audience because local advertisers will value an additional local listener more than an additional out-of-market listener.

in the same MMC have moved further apart over time this could appear as an ownership effect in my regressions because the proportion of commonly owned stations increases over the sample period. Alternatively the Williams et al. finding could be because they do not allow for common ownership to increase differentiation only between stations in the same MMC. I therefore include interactions between the week dummies and the $SAME\_MARKET$ dummy. If common ownership does not play a role in increasing differentiation within MMCs then the $SAME\_MKTOWNER$ coefficient is now expected to be zero. Instead, the coefficient is almost unchanged from the original specification, indicating that common ownership does increase differentiation within MMC.

Entry and exit by other stations could clearly change the optimal locations of stations which remain in the MMC. In check 5 I include dummies for the number of stations in the MMC of each station in the pair and an additional set of dummies for the number of stations when both stations are home to the same market. The $SAME\_MARKET$ effect is not identified even without category-pair fixed effects. The ownership coefficients scarcely change at all indicating that the coefficients do not simply reflect differences in or changes in the number of stations in an MMC. Check 6 also repeats the regressions using only those pairs where both stations come from MMCs containing at least three stations. The results, particularly when I include fixed effects, show that the variety-increasing effects of stations mergers within MMCs also hold in MMCs with more than two stations. Check 7 repeats the regressions using stations which are the only stations in their MMC to investigate where there is more homogenization of programming on these stations (which are mainly in smaller metro-markets) whose music choices should be less affected by the need to differentiate themselves from other stations in their market. The $SAME\_MARKET$ and $SAME\_MKTOWNER$ coefficients are not identified. The $SAME\_REGION$ and $SAME\_OWNER$ coefficients are larger in absolute size and more significant than in the basic specification, but the implied homogenization effect due to common ownership is still relative small (this is also true for Measure 2).

Check 8 provides further assurance that the possible dependence between the residuals for different category-pairs does not lead to the significance of the result within-MMC common ownership increases variety being exaggerated. I estimate the regressions using a very small sub-sample of the data in which each station appears in only one pair in a category. Standard errors are clustered on the category-pair to allow for serial correlation in distances across weeks for the same pair. The selection of the sub-sample is described beneath the table and there are only 32 (94) pairs which are home to the same (different) MMC which change whether they are commonly owned. The sums of the $SAME\_OWNER$ and $SAME\_MKTOWNER$ coefficients are significant at the 1% level without fixed effects, and, as in columns (1) and (3) in Table 3.6, significant at the 2% level with fixed effects.

Alternative Specifications

Table 3.9 presents the results from specifications using MMC average distances and the distance of each station from the centre of its category. These specifications also act as additional robustness checks because they do not suffer from problems in calculating the correct standard errors.

MMC Average Distances Columns (1)-(3) of Table 3.9(a) report the results from regressing the average distance between pairs of stations in an MMC on week dummies, category dummies, dummies for the number of stations in the MMC (interacted with category dummies), dummies for the number of stations in the airplay data (also interacted with category dummies) and an ownership variable. The reported $MEAN\_SAME\_MKTOWNER$ and $ANY\_SAME\_MKTOWNER$ coefficients come from separate regressions. The coefficients on $MEAN\_SAME\_MKTOWNER$ are, not surprisingly, very similar to the sum of the $SAME\_OWNER$ and $SAME\_MKTOWNER$ coefficients reported in Table 3.5. The $ANY\_SAME\_MKTOWNER$ coefficient is smaller, but still significant, because the dummy is 1 when any pair of stations in the MMC (in the airplay sample) is commonly owned and we know from Table 3.5 columns (4)-(6) that the distance between commonly owned stations and non-commonly owned stations is not affected by the common ownership.

Columns (4)-(6) include fixed effects for the group of stations in the MMC in the airplay data. As there is a new fixed effect when any station in the MMC enters or exits the airplay sample or changes category, there are only 35 changes which identify the $MEAN\_SAME\_MKTOWNER$ coefficient. The time series around each of these changes is also shorter. This explains why the coefficients are smaller and less significant than those in Table 3.6. The Measure 2 coefficients are insignificant. The coefficients are very similar in columns (7)-(9) when I also include dummies for the total number of stations in the MMC to control for entry and exit of stations which are not in the airplay sample.

Distance of Each Station from the Centre of its Category Columns (1)-(3) of Table 3.9(b) report the results from regressing the distance of each station from the centre of its format-category on week dummies, category dummies, an $ANOTHER\_IN\_MMC$ dummy (1 if there is another station in the MMC whether it is in the airplay sample or not) and $NUMBER\_OWNED\_IN\_MMC$ (a count of the stations the owner has in the MMC). The regression tests whether common ownership is associated with more specialization in particular kinds of music within the category. The coefficients show that a station locates further from the centre (more specialization) when there are other stations in the MMC and when it is commonly owned with more stations.[25]

Columns (4)-(6) include dummies for the station's format. Consistent with the pair results, the increased specialization is only partly captured by station formats. Columns (7)-(9) report the results when I include station-category fixed effects. The $ANOTHER\_IN\_MMC$ effect disappears. This is not surprising because the number of stations in an MMC is primarily determined by market size which does not change significantly over the sample period so it is hard to separately identify this effect from the coefficient on the station-category dummy. The ownership effect is smaller with the fixed effects but it is still significant at the 5% level for all three location measures. The coefficients are also similar in (not reported) regressions where I include dummies for the number of stations in the MMC (interacted with category dummies) to control for station entry and exit.

3.4 Does Common Ownership Increase Station Listenership?

I now examine how changes in ownership have affected station listenership. There are two motivations for examining listenership. First, if the primary effect of common ownership of stations in an MMC is to internalize business stealing then we should not only expect these

[25]The distance each station moves from the centre of the category is less than half of the distance stations move from each other because, in practice, stations are not arranged symmetrically around the centre.

stations to increase variety but also to increase their combined listenership. Second, changes in listenership may also give some indication of whether the growth of common ownership has tended to increase listener welfare. There may not be a monotonic relationship between aggregate station listenership and listener welfare when stations change their locations in product space. The welfare of listeners whose preferences were better matched to what stations played before the change will fall and the welfare of listeners with preferences better matched to what is played after the change will increase. The change in aggregate welfare will then depend on the intensity of preferences of the two groups but the change in listenership will depend on their listenership elasticities with respect to what is played.[26] However, in the absence of more detailed data on listener preferences, aggregate listenership is the best gauge of listener welfare which is available.

Section 3.4.1 introduces the listenership data. In Section 3.4.2 I use the station pairs from the airplay data to examine how the listenership of pairs which are home to the same MMC changes in response to changes in whether the pair is commonly owned. Section 3.4.3 presents the results from estimating a nested logit model of listenership using a much larger sample of stations and markets.

3.4.1 Listenership Data

I briefly describe the main features of the listenership data. Complete details of this data, data on station and market characteristics and data sources are given in Appendix C. Summary statistics are presented in Table 3.10 and are discussed in the relevant sections of the text.

Arbitron collects listener diary data from a large number of metro-markets (currently 287) producing 4 quarterly ratings reports (Winter, Spring, Summer and Fall) for large markets and 2 (Spring and Fall) for small markets. A commercial station is rated (listed in the report) if a significant proportion of diary-keepers report that they listened to it. I use two share numbers. The first is each station's share of total radio listening (including to non-commercial or non-rated stations) in its market. This share is calculated based on listening by individuals aged 12 and above (12+) during an average quarter-hour (AQH) in a broadcast week of Monday-

[26]Spence and Owen (1977) discuss how consumers with intense preferneces but low elasticities are likely to be underserved in broadcasting markets where consumers do not pay prices.

Sunday 6am-12pm. The second number is average proportion of the 12+ population in the market listening to any radio station during an AQH for the same broadcast week (known as the APR).

I use AQH share data for 281 different metro-markets from the Spring and Fall reports for Spring 1996 to Fall 2002 and from the Winter and Summer reports for large markets from 2000 to 2002.[27] The panel of markets is not balanced because more markets are surveyed each year. I also collected APR data for the Spring and Fall surveys from Spring 1996 to Fall 2002 although this data is missing for a few individual market-quarters.

3.4.2 Listenership of Station Pairs in the Airplay Data

In this section I use the station pairs from the airplay data which are home to the same MMC and examine how their listenership changed in response to changes in whether the pair were commonly owned. Two different measures of the pairs' combined listenership are used as dependent variables. The first measure is the pair's combined share of total radio listening in the stations' home market during the ratings quarter ($SHARE\_LISTENING$), i.e., the sum of the AQH 12+ shares. The second measure is the average proportion of the 12+ population in the home market listening to either of the stations ($SHARE\_12+$), calculated as the AQH 12+ share multiplied by the market APR. I use these measures both in levels and logs. There is, at most, one observation per pair per ratings quarter.[28] I only have APR observations for the Spring and Fall surveys so there are, at most, two observations per pair per year for the second measure. Summary statistics are presented in Table 3.10(a). As I only include pairs from the same market, standard errors are clustered at the level of the metro-market.

In Table 3.11(a) I regress the pair listenership measures on a $SAME\_MKTOWNER$ dummy together with ratings quarter and category dummies. The $SAME\_MKTOWNER$ dummy is the minimum of the $SAME\_MKTOWNER$ dummy defined in Section 3.3 for the pair during the relevant ratings period, so that if the stations become commonly owned during

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

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

the ratings period the dummy is 0. In these regressions the $SAME\_MKTOWNER$ coefficient is partly identified by cross-sectional differences in pair listenership. The $SAME\_MKTOWNER$ coefficients are positive and significant at the 1% level. The coefficient in column (2) implies that pairs which are commonly owned have, on average, a combined share of radio listening in their market which is 11.5% greater than pairs which are not commonly owned. Of course, this result could simply reflect the fact that owners of multiple stations are likely to buy stations with larger listenership.

In Table 3.11(b) I repeat the regression including category-pair dummies so that the ownership effect is identified from changes in listenership when pairs change whether they are commonly owned. There are 35 such changes in the data.[29] The $SAME\_MKTOWNER$ coefficient is positive in all of the regressions but it is only statistically significant at the 10% level when the dependent variable is the log of $SHARE\_12+$. The column (4) coefficient implies that a pair's total audience increases by 3.3% when the pair becomes commonly owned. The column (4) coefficient is larger than the column (2) coefficient and this is consistent with some of the audience increase coming from people who would not otherwise listen to the radio. The lack of statistical significance is not surprising given the small number of relevant ownership changes and the fact that I have a maximum of 12 observations per pair here rather than 45 observations per pair in Section 3.3. Given this, the coefficients seem to provide some preliminary evidence that common ownership of stations in an MMC increases listenership, consistent with the primary effect of common ownership being the internalization of business stealing.

These regressions do not control for changes in the number or identity of the other stations rated in the MMC. If common ownership is associated with a reduction in the number of other stations in the MMC then the listenership of the commonly owned stations might increase simply because of a reduction in the number of close substitutes rather than because the merged stations provide greater variety or better quality programming. In Table 3.11(c) I repeat the regressions in Table 3.11(b) but I now also include dummies for the number of home to market stations in the MMC. The $SAME\_MKTOWNER$ coefficients are slightly

[29] There are fewer pair ownership changes than in Section 3.3 because for some pairs I only have data outside the Spring and Fall ratings periods for 1998 and 1999 and for some other pairs the stations become commonly owned in one ratings period and cease to be commonly owned in the next rating period so that the $SAME\_MKTOWNER$ dummy is 0 for both of these periods.

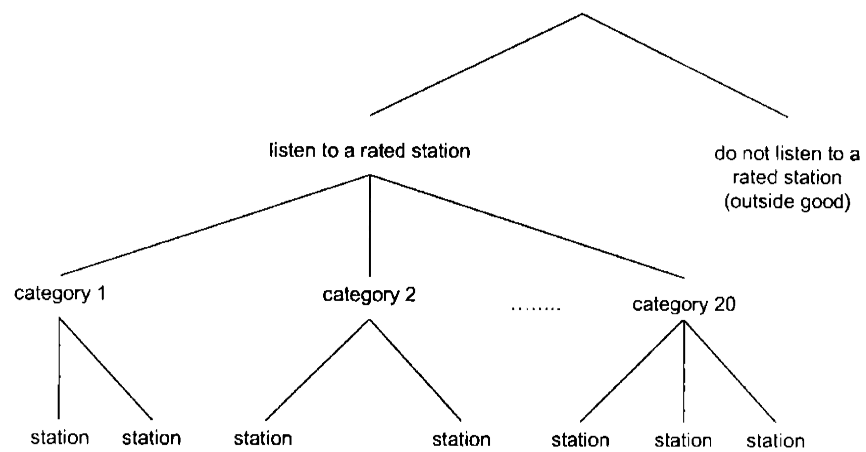
smaller in magnitude than in Table 3.11(b) and the coefficients are even less significant. In Table 3.11(d) I include dummies for the identity of group of stations in the MMC so that there is new dummy whenever any station (in the airplay sample or not) enters or leaves the MMC. There is variation in whether small stations are rated at all and in which categories they appear, so this adds 597 different identity dummies to the regression in addition to the category-pair and ratings quarter dummies. There are only 20 ownership changes where the identity of the stations is unchanged around the ownership change which can identify the ownership coefficient. The number of observations around these changes is also typically short. The $SAME\_MKTOWNER$ coefficients fall again and are now very insignificant. However, ignoring statistical significance, the coefficients all imply that common ownership of stations in the same MMC increases their listenership by between 1% and 1.6%. I interpret this as providing further, albeit very weak, support of the hypothesis that common ownership increases listenership.

3.4.3 Nested Logit Model of Station Listenership

To provide additional evidence of the effects of ownership on audiences I estimate a discrete choice nested logit model of station listenership and use data from stations in all categories, including other music categories (e.g., Classical) and non-music categories (e.g., News and Talk). A nested logit demand model defines a simple relationship between the average quality of a product in the eyes of consumers (mean utility), the product's market share, the combined market share of various groups of products (nests) and the proportion of potential consumers who do not consume any of the products (described as choosing the outside good).[30] The relationship holds independent of changes in the quality or number of other products, so such changes are implicitly controlled for by the (very strong) functional form assumption. An increase in a product's share, relative to the shares of the nests and of the outside good, implies that a product's quality must have increased. I examine how stations' implied qualities are affected by a number of aspects of station ownership. This does not imply that I am necessarily

[30]For additional discussion of the assumptions behind the nested logit model, see Berry (1994), Greene (1997, p. 865-871) and Nevo (2000). Hausman and Wise (1978) present a framework which allows for estimation of the correlation of preferences for different products which is less dependent on the assumed functional form. However, this framework is difficult to apply when the number of different products is large as it is here.

Figure 3-4: Nesting Structure for the Nested Logit Model of Station Listenership



assuming that ownership affects absolute station quality in the sense of a vertical differentiation model; instead, I use a nested logit because it is a convenient way to examine the effects of ownership and to see how they affect the distribution of listenership amongst stations and categories, and the total amount of radio listening.

Figure 3-4 shows the nesting structure. I assume that stations in the same category are closer substitutes, on average, than those in different categories, and that stations in different categories are closer substitutes with each other than with the outside good. Consumption of the outside good is defined as "a person aged 12 or above spending time during the broadcast week not listening to a commercial radio station with a non-zero share in Arbitron's market report".[31]

The mean utility of listening to station s is a function of a number of variables. X_{sm} are observed station s characteristics in market m which can differ across stations in an MMC, such as ownership or transmitter power. ξ_{sm} reflects the effects of s's unobserved characteristics, such as DJ ability. $X_{c_s m}$ are characteristics of s's category c_s which may differ with market m characteristics. These do not differ across stations in an MMC. X_m are market m characteristics which affect the attractiveness of listening to any rated commercial station.

Given the nesting structure and normalizing the mean utility of the outside good to zero,

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

the share of individuals in market m listening to station s in ratings quarter t (s_{smt}) is

$$s_{smt} = \frac{e^{X_{smt}\beta_1+\xi_{smt}}}{\sum_{r\epsilon c_s mt} e^{X_{rmt}\beta_1+\xi_{rmt}}} \frac{e^{X_{c_s mt}\beta_2+\tau I^{c_s}_{mt}}}{\sum_{c=1}^{C} e^{X_{cmt}\beta_2+\tau I^{c}_{mt}}} \frac{e^{X_{mt}\beta_3+\delta I^{in}_{mt}}}{1+e^{X_{mt}\beta_3+\delta I^{in}_{mt}}} \tag{3.7}$$

$$\text{where } I^c_{mt} = \ln\left(\sum_{r\epsilon cm} e^{X_{rmt}\beta_1+\xi_{rmt}}\right) \text{ and } I^{in}_{mt} = \ln\left(\sum_{c=1}^{C} e^{X_{cmt}\beta_2+\tau I^c_{mt}}\right) \tag{3.8}$$

The βs, δ and τ are parameters and the Is are "inclusive value" terms which reflect the attractiveness of the stations in the lower branches of the tree structure.[32] Following the logic of Berry (1994), (3.7) can be rearranged to give a linear estimating equation

$$\ln s_{smt} - \ln s_{omt} = (1-\delta)\ln(s_{in,csmt}) + (1-\delta\tau)\ln(s_{c,smt}) + X_{smt}\beta_1\tau\delta + X_{c_s mt}\beta_2\delta + X_{mt}\beta_3 + \tau\delta\xi_{smt} \tag{3.9}$$

s_{omt} is the share of the outside good, $s_{c,smt}$ is s's share of listening to stations in its MMC and $s_{in,csmt}$ is s's MMC's share of rated commercial radio listening (the inside goods). Consistency of the nesting structure with utility maximization implies that the inclusive value parameters δ and τ lie in the unit interval (McFadden (1981)). This implies that the $\ln(s_{c,smt})$ coefficient should be greater than the $\ln(s_{in,csmt})$ coefficient and that both should lie in the unit interval.

In equation (3.9) the unobserved ξ_{smt} will be correlated with $s_{c,smt}$ and $s_{in,csmt}$. As suggested by Berry (1994), the observed characteristics of other stations in the market can be used as instruments for $\ln(s_{c,smt})$ and $\ln(s_{in,csmt})$ under the assumption that station s's unobserved characteristics are uncorrelated with the observed characteristics of other stations.[33]

A feature of station ownership is that radio groups tend to own relatively large stations. As I do not have an instrument for who owns which stations I use station fixed effects in (3.9) and identify the effects of ownership from changes in listenership in response to changes in

[32] An additional note on the notation: C is the number of different categories, and $r\epsilon cm$ are the set of stations in category c in market m. The three terms in (3.7) are respectively the probability of choosing s conditional on choosing c_s, the probability of choosing c_s conditional on choosing an inside station and the probability of choosing an inside station rather than the outside good.

[33] The observed characteristics of other stations should be correlated with $s_{c,smt}$ and $s_{in,csmt}$ because when other stations have better characteristics s's share of its MMC and its MMC's share of listening to all of the rated stations in the metro-market will tend to be lower. I note that if stations select their category based on information about other stations unobserved characteristics the instruments will be invalid. I experimented with only using instruments which are more clearly exogenous such as population and the characteristics of out of market stations. However, these produced substitution patterns in some specifications which were not consistent with utility maximization.

ownership. To be precise, I use station-market-category fixed effects so that a station's quality can be different in different markets in which it is rated by Arbitron and its quality can change if it switches to a new category.

As I will show, the inclusion of fixed effects increases the amount of implied substitution across categories compared to estimates from the cross-section of markets. There is a simple reason for this. Controlling for systematic differences, such as the popularity of Country music in the South, the total listenership of different categories is fairly similar across metro-markets and varies little with the number of stations in the category or the distribution of market shares across the stations. In a nested logit model this kind of pattern is explained by the categories being poor substitutes for each other.[34] On the other hand, with fixed effects the substitution patterns are identified from changes in the set of stations in a market or MMC over time. The main source of variation comes from stations switching category which happens frequently for smaller stations. However, many of these switches may involve relatively small changes in airplay (for example, a switch from Classic Hits (in the Rock category) to Classic Rock (in the Album Oriented Rock/Classic Rock category)) and this kind of switch may result in only small changes in station listenership. In a nested logit model this will be rationalized by by categories being relatively good substitutes for each other.

Different substitution patterns give different predictions for what should happen if two stations within an MMC merge and their quality increases, with the qualities and categories of all of the other stations staying the same. If substitution between categories is assumed to be high then a large number of listeners to the new stations should come from other categories and the outside good. If this assumption is incorrect and the merged stations will only attract a small number of listeners from outside their category then this will be rationalized by common ownership having only a small effect on quality.

I present two different sets of estimates. I first estimate (3.9) including station-market-category fixed effects. The substitution patterns imply a fairly high degree of substitution between categories and the implied effect of common ownership within a metro-market or MMC on station quality and listenership is positive but quite small. As an alternative, I estimate

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

substitution patterns from a cross-section and then estimate the effects of ownership assuming that these substitution patterns are correct. These estimates imply common ownership within an MMC leads to much larger increases in station listenership. I discuss whether one particular set of estimates should be preferred in the conclusion. In both sets of estimates the effect of common ownership of stations in different metro-markets is very small in magnitude and statistically insignificant.

Data Sample and Variable Definitions

I use data from the Spring and Fall Arbitron surveys 1996-2002 for the complete set of metro-markets and stations for which I have station share and market radio listenership data. This gives 94,770 station-market-quarter observations from 281 different metro-markets.

The main specifications use four different ownership variables defined based on the transaction history in the BIAfn database.[35]

DUM_OWNER_MMC is a dummy equal to 1 if the station is commonly owned with another station rated in the MMC. The stations need not be home to the metro-market. If common ownership of stations in the same MMC increases their listenership the coefficient should be positive.

$OWNER\_MKT$ is the number of stations an owner has in the metro-market in any category. This includes stations which are rated in the metro-market but are not home to the metro-market. It is designed to pick up any effects of ownership that are not category-specific and so are less likely to be related to product differentiation. DUM_OWNER_MKT is a dummy equal to 1 if the owner has at least two stations in the metro-market.

$OWNER\_CATEGORY$ is the number of different stations an owner has in the category across all rated metro-markets. The coefficient should be positive if ownership of multiple stations in different markets leads to better quality programming, for example through shared research. I use the natural logs of $OWNER\_MKT$ and $OWNER\_CATEGORY$ in the regressions because any effects are unlikely to be linear in the number of stations owned.

[35] As explained in Section 3.3.3 the BIAfn data lists the transaction announcement date rather than the completion data for all but each station's most recent transaction. The coefficients change very little if I assume that deals were completed several months after the date listed in the BIAfn database.

Table 3.10(b) presents summary statistics for these variables. In the regressions the effects of ownership are identified from changes in ownership. Fortunately, ownership consolidation since 1996 provides 5,298 changes in ownership for the stations in the sample. The average values of $OWNER\_CATEGORY$, $OWNER\_MKT$ and DUM_OWNER_MMC grow from 2.5, 2.1 and 0.140 respectively in Spring 1996 to 26.6, 4.2 and 0.269 in Fall 2002.

In estimating (3.9) one would ideally like to control for changes in station technical characteristics, such as transmitter power, and changes in market characteristics, such as the age structure and commuting times, which affect the total level of radio listening. Unfortunately I only have data on these variables for Fall 2001 so I have to assume that these characteristics are fixed over time in which case their effects are not separately identified from the coefficients on the station-market-category dummies. In practice, relative market characteristics (such as the proportion of the population aged 65 and above) would not have changed much from 1996 to 2002. If common owners tend to improve station technical characteristics then the effects of these changes will be included in the coefficients on the ownership variables.

I use the sums of the station characteristics listed in Table 3.10(b) for the other rated stations in station s's MMC and the other stations in s's metro-market as instruments for $\ln(s_{c,smt})$ and $\ln(s_{in,csmt})$.[36] A few stations have missing data for characteristics such as transmitter power so I also include, as additional characteristics, dummies indicating that stations have a particular characteristic missing.

Results with Substitution Patterns Estimated from Within Market Entry and Exit

Table 3.12(a) presents the results of estimating (3.9) with station-market-category dummies (fixed effects). Columns (1)-(6) present results from specifications including different combinations of the ownership variables. The $\ln(s_{c,smt})$ coefficient is greater than the $\ln(s_{in,csmt})$ coefficient and both are in the unit interval so the model is consistent with utility maximization. These coefficients are also very similar across specifications. The ownership coefficients also

[36]Note that I am using Fall 2001 station characteristics to form instruments for $\ln(s_{c,smt})$ and $\ln(s_{in,csmt})$ in other ratings quarters. There could therefore be some mismeasurement in the instruments. However, this should not be a problem unless the measurement error in other stations' characteristics is correlated with the time-varying component of station s's error in equation (3.9). Estimated substitution patterns using only those characteristics which can be assumed not to change (such as station bands (AM,FM), age and home market) are fairly similar.

show a similar pattern across the specifications. Common ownership of stations in the same category but different metro-markets is positive but insignificant in all of the specifications. Common ownership of stations in the same metro-market but different categories has a positive and significant effect on mean utility, while common ownership of stations in the same MMC has a smaller effect and it is generally not significant.[37]

I illustrate the size of the within-MMC effects implied by the column (1) coefficients by calculating listenership is predicted to change in response to two hypothetical ownership changes in Boston in Fall 2001. The first example involves the only two Urban stations in the market, WBOT-FM and WILD-AM. In Fall 2001 these were commonly owned by Radio One which owned no other stations in the market. Suppose that they were sold to separate independents so that both the DUM_OWNER_MKT and DUM_OWNER_MMC become zero. The coefficients imply that the share of each of these station would fall by 2.2%. 69% of this listening reduction would go the 34 rated stations in other categories with the remaining 31% of the reduction lost to any rated station. Of course, if there are more stations in a category then the effects outside of the category are smaller. To illustrate this, the second example comes from the Rock category with 8 stations. Greater Media owned WBOS-FM and WROR-FM along with some non-Rock stations. Suppose that Greater Media sold WBOS to an independent but kept WROR. WBOS's audience would fall by 2.0% but WROR's audience would increase by 0.8% because its quality would increase (for WROR DUM_OWNER_MKT remains 1 and DUM_OWNER_MMC changes from 1 to 0 and the coefficient on this dummy is negative). 15% of the net reduction in listenership to the pair would go to the 6 other Rock stations, 56% would go to stations in other categories with the remaining 29% lost to any rated station. Thus, even when there are several other stations in the same category, these estimated substitution patterns imply that if the quality of a station drops more listeners stop listening to any rated station than switch to other stations in the same category.

Column (7) contains the results from repeating the column (1) specification but also including an interaction between the ownership effects and a dummy for whether the station-quarter is from the airplay sample. There are 6,772 station-quarters and 14,447 station-market-quarters

[37]When two stations in the same MMC are in common ownership, DUM_OWNER_MKT and DUM_OWNER_MMC are both equal to 1 so the relevant coefficient for the total effect in column (1) is the sum of the coefficients.

from the airplay data because many of the stations in the airplay data are rated in more than one metro-market. The estimated effect of common ownership within a metro-market on listernership is significantly larger for the airplay stations than for the rest of the sample.

Results with Substitution Patterns Estimated from Fall 2001 Cross-Section

Table 3.12(b) column (1) presents the results of estimating (3.9) using data from Fall 2001, the quarter for which I have accurate station technical characteristic and market characteristic data. I do not include station-market-category fixed effects, so the effects of market characteristics, such as demographics and region dummies, station characteristics and category characteristics are identified. I include a full set of interactions between category dummies and market characteristics to allow, for example, Spanish stations to be more popular in markets with a large Hispanic population. The instruments, the sums of characteristics of other stations in the metro-market and in the MMC, are the same as before.

The $\ln(s_{in,csmt})$ and $\ln(s_{c,smt})$ coefficients are consistent with utility maximization and are precisely estimated. They are larger than the same coefficients in Table 3.12(a) which implies less substitution between categories. This illustrates the effect of the different identification strategy. The coefficients on the characteristics also make intuitive sense. For example, there is more listening to commercial radio in markets with longer commuting times and more powerful transmitters are associated with higher station quality. In column (2) I show that the coefficients are very similar when I estimate (3.9) using data from all quarters but without station-market-category fixed effects. The quarter dummies illustrate the decline in total radio listening over this period reflecting the availability of substitutes for radio such as in-car CD players.

I use the estimates of $(1-\delta)$ and $(1-\delta\tau)$ from column Table 3.12(b) column(1) to calculate $\ln s_{smt} - \ln s_{omt} - (1-\delta)\ln(s_{in,csmt}) - (1-\delta\tau)\ln(s_{c,smt})$ for each station-market-quarter. I then regress this measure on the ownership variables, station-market-category dummies and ratings quarter dummies. The results are shown in Table 3.12(c) for specifications equivalent to Table 3.12(a). Common ownership of stations in the same metro-market and category is now estimated to have a significantly larger effect than common ownership of stations in the same metro-market but different categories, although this also has a positive effect. Common ownership of stations in different metro-markets does not have a significant effect and the sign of the coefficient varies across specifications. The effects for the airplay sub-sample are found to be quite similar to the effects for the rest of the sample.

The coefficients imply larger effects of ownership on station listenership as can be seen by recalculating the effects of the hypothetical ownership changes. The first example is the sale of the Urban stations WBOT-FM and WILD-AM to separate independents. The coefficients imply that the share of each of these stations would fall by 7%. 87% of this listening reduction would go to the 34 rated stations in other categories with the remaining 13% of the reduction lost to any rated station. The second example was a sale by Greater Media of WBOS while retaining another Rock station, WROR. The coefficients imply that WBOS's audience would fall by 11.6% and WROR's would fall by 7.8%. WROR's audience falls here because its DUM_OWNER_MMC dummy changes from 1 to 0 and this coefficient is positive. 43% of the net reduction in listenership to the pair would go to the 6 other Rock stations, 49% would go to stations in other categories with the remaining 8% lost to any rated station. The cross-sectional substitution patterns imply that, with several category competitors, a reduction in station quality results in more listeners switching to other stations in the category than stop listening to rated stations.

Is it Variety which Increases Listenership?

The pair regressions and the nested logit results provide some evidence that when stations in the same market become commonly owned their listenership increases. However, this might not happen because product differentiation increases but rather because the stations improve some aspect of absolute station quality. Two examples of a quality change would be the hiring of better DJs or a reduction in the number of commercial breaks because the merged stations have greater market power in the advertising market. While listeners might like a reduction in commercials, it would reduce the welfare of advertisers.

If product differentiation increases listenership then we would expect the effect of common ownership to be largest for stations in the same category. The nested logit results using cross-sectional substitution patterns suggested that this might be the case. I now present the results of a test, which uses the fact that some stations are rated in multiple markets, to provide evidence that the results in Table 3.12(c) are more consistent with listenership increasing due to product differentiation (variety explanation) than a reduction in advertising (market power explanation) or an increase in some other aspect of quality.

Assume that a station's differentiation or advertising decisions are based only on considerations in its home MMC.[38] Suppose that two stations, A and B, have the same home MMC (metro 1), that they become commonly owned and that their owner owns no other stations. In addition, A is rated in metro 2 but B is not. First, suppose common ownership leads to fewer commercials. All else equal, this should increase the quality of each station for listeners and their audience in any market in which either station is rated. For example, A's audience in metro 2 should increase when it has fewer commercials because of common ownership in metro 1. Second, suppose that A and B do not change the number of commercials but move apart in product space to internalize business stealing. All else equal, this should increase their audience in metro 1. However, it is not clear that A's audience should increase in metro 2 because A's new location does not internalize business stealing with any station in that market. Depending on the location of other stations in metro 2 A's audience could increase, decrease or stay the same. Following this logic, I test whether common ownership of a station in its home MMC increases its listenership in markets in which all of its commonly owned home MMC sister stations are absent. If it does, the data is consistent with the market power explanation, but if it does not then the data is inconsistent with the market power explanation but consistent with the variety explanation.

I define two new dummies. DUM_OWNER_ATHOME equals 1 if the station is commonly owned in its home MMC with another station home to the same MMC. $DUM\_OWNER\_SAMEHOME$ equals 1 if the station is rated in the MMC along with another station which has the same owner and the same home metro-market.[39] These dummies are included in addition to DUM_OWNER_MMC which now measures any effect associated with two rated stations having the same owner when they are not home to the same market and they are not commonly owned in their home MMCs. If a station is only affected by conditions in its

[38] The result of robustness check 3 in Section 3.3.5 provides some evidence that differentiation is affected by common ownership only in a station's home market.

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

home market then this coefficient is expected to be zero. Under the market power explanation, the DUM_OWNER_ATHOME coefficient should be positive and significant and the $DUM\_OWNER\_SAMEHOME$ coefficient should be insignificant. The variety explanation suggests the opposite pattern.

Table 3.13(a) column (1) presents the results when I take substitution patterns from the Fall 2001 cross-section and do not allow for different effects for stations in the airplay sample. The coefficient on $DUM\_OWNER\_SAMEHOME$ is positive and significant and the DUM_OWNER_ATHOME coefficient is very close to zero. Stations which become commonly owned in their home MMC do not, on average, increase their listenership in markets where their home market sister stations are absent. This is true even if there is another station with the same owner but from a different home market (Table 3.13(b) test 1). On the other hand, if a home MMC sister station is present then a station does, on average, increase its listenership (test 2). This pattern is consistent with the variety explanation but not the market power explanation.

Column (2) presents the same results when I allow the stations in the airplay sub-sample to have different effects. It is important to check that the results hold for the airplay sample because this is the group for which I know that, on average, common ownership increases differentiation between stations which are home to the same MMC. There are so many coefficients reflecting MMC ownership that most of them are individually insignificant. However, the tests listed below the table show that the same pattern holds for both groups of stations: common ownership only increases listenership in the presence of home market sister stations.

3.5 Conclusion

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

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

The second issue is whether it matters that I do not use an instrument for changes in station ownership. The danger is that something unobserved could cause changes in station ownership, location and listenership which I will misinterpret as a causal effect of ownership changes. This possibility cannot be ruled out completely. However, it is hard to imagine what factor, other than the preceding ownership change, would lead an Adult Contemporary station to start playing less of Enya and more of Celine Dion which is the kind of change I observe in the data. I also note that increased differentiation of playlists to avoid business stealing is consistent with comments made by station programmers of commonly owned stations (see, for example, footnote 3). Finally, most of the station ownership changes which I observe result from the purchase of one radio group owning multiple stations by another group. This makes it unlikely that an ownership change for an individual station would be correlated with something which would also make it change location.

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

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Appendices

A. Projection of Artists into the 2-Dimensional Plane

As described in Section 3.3.2, I project artists into a 2-dimensional plane in order to calculate stations' Measure 3 locations. The first stage of the process is the calculation of the distance between each pair of artists located in high-dimensional station space using the angle (in radians) between the artist location vectors as the measure of distance. I then project each artist into a 2-dimensional plane. Ideally I would choose the locations of all of the artists simultaneously to minimize (3.3). However, this is not feasible because of the large number of artists in each category-week (on average, over 1,200) and there are also 315 category-weeks for which artists need to be located. (3.3) may also have multiple local minima so it is necessary to start the minimization from multiple different starting points.

The procedure used is as follows:

1. take the 30 most played artists in a category-week (on average, these account for 42% of plays) and calculate the high-dimensional station space distances (d_{ij}) between each pair of these artists;

2. locate these stations in the plane by minimizing (3.3) with respect to their locations. The most played artist is fixed at the origin and the second most played artist is fixed to be on the x-axis. As there may be multiple local maxima I use 11 different sets of starting values and use the estimates which give the lowest value of the objective function . The first set of starting values groups all of the artists together at the origin while the other sets draw each artists' initial locations from a bivariate independent standard normal distribution;

3. calculate the high dimensional station space artist pair distance between the 31^{st} most played artist and each of the 30 most played artists;

4. locate the 31^{st} artist by minimizing (3.3) with respect to the location of the 31^{st} artist taking the location of the 30 most played artists (from step 2) as fixed. This is done using a single starting point which has the 31^{st} artist initially located at the average coordinates of the 30 most played artists;

5. repeat steps 3 and 4 for the 32^{nd} artist but now calculating the distances between the 32^{nd} artist and the 31 most played artists and treating the location of the 31 most played artists as fixed. This step is repeated for all artists played more than 10 times by stations in the category-week.

There are two checks on whether this is a sensible procedure to get reasonable artist locations. First, one can look at the resulting locations of different artists and check that they appear to be sensible (Figure 3-1). Second, one can try a number of different procedures and check that they produce similar implications for where artists and stations are located. For example, I repeated the location of the 30 artists in Figure 3-1 using 1,300 different starting points rather than 11. The pattern of artists and the resulting distances between pairs of stations were very similar. I also tried simultaneously locating the 50 most played artists rather than the 30 most played artists. This is much slower because the time taken to minimize (3.3) is not linear in the number of parameters. The locations of the artists, the distance between the stations and the value of the objective function were similar to those calculated using my procedure.

B. Standard Errors in the Pair Distance Regressions

In this Appendix I describe a simulation exercise designed to check whether the size of significance tests of the coefficients in the pair distance regressions in Sections 3.3.5-3.3.5 is approximately correct. Recall that the residual for a pair of stations ij in week w may be correlated with the residual for any other pair involving either i or j because i or j's location affects the calculation of both pair distances. In addition, the residual may also be correlated with the residual for the same pair in different weeks because most stations only change their playlists gradually. As I calculate distances between all of the stations in a category in a given week, I try to allow for the dependence in the data by clustering the standard errors at the category level. However, because the resulting number of clusters is small (7), it is important to check whether the test of significance based on these standard errors are of approximately the correct size.[40]

Simulation Exercises

I design two simulation exercises so that the structure of the correlations in the residuals in the simulations is similar to the correlations in the actual data.

Simulation Exercise without Category-Pair Dummies In each repetition of the simulation, each station keeps its actual characteristics (home market, music category, ownership history) but is randomly assigned locations by randomly drawing, without replacement, a station from its category and giving it the locations in, every week, of the drawn station. For example, suppose that i, j, k, x, y and z are AC stations and that i, j and k draw the locations of x, y and z respectively. In this case the new ij, ik and jk pair distances will be the xy, xz and yz pair distances from the original data in every week. With random assignment of locations there should be no systematic expected relationship between station pair characteristics and the pair distances. I then repeat the regressions in columns (1, Measure 1) and (3, Measure 3) of Table 3.5 and check whether the estimated coefficients are significant at the 1,5 or 10% significance levels assuming that the t-statistics have a t-distribution with 6 degrees of freedom (the number of clusters minus 1). I calculate the proportion of repetitions in which I reject that the null hypothesis that each of the coefficients of interest are zero, based on 500 repetitions: if the tests have their nominal size then I would expect, for example, to reject the null hypothesis that a coefficient is zero at the 5% significance level approximately 5% of the time.

Performing such a large number of repetitions for the entire sample is infeasible. I therefore use data from the year 2001 and use the 807 stations for which I have data for every week of that year. A balanced panel also means that the number of observations is the same across different repetitions of the simulation.

[40]Donald and Lang (2001) and Wooldridge (2003) discuss the complications which arise when the number of clusters is small.

Simulation Exercise with Category-Pair Dummies This exercise works in an identical way to the exercise without category-pair dummies but the sample of data used is different in order to include enough pairs with ownership changes. I keep stations which are in the data for at least 35 weeks (out of a possible 45) and use data from every fourth week from July 1998 through November 2001. I also drop all the Oldies stations (there are no pairs in this category which change whether they are commonly owned) so the t-statistics are now assumed to have a t distribution with 5 degrees of freedom.

Simulation Exercise Results

Tables 3.A1(a) and (b) report the results of the exercise without category pair dummies for Measures 1 and 2 respectively while Tables 3.A1(c) and (d) report the results with category pair dummies. In each table the first column reports the estimates using the sub-sample of actual data used in the exercise.

In each of the tables we see that the rejection rates are close to the nominal size of the test for each of the coefficients and for each of the distance measures, although the rejection rates appear to be slightly too high for the regressions without pair dummies. For example, the hypothesis that the $SAME\_MKTOWNER$ coefficient is zero is rejected at the 10% level in 11.8% of the repetitions. However, recall that the main result from these regressions, that within market common ownership increases variety, is significant at the 1% level for Measures 1 and 3.

C. Data used in analysis of listenership

This Appendix details the sources of data used in Section 3.4 and provides some additional definitions. The major sources are BIAfn's *Media Access Pro* database (BIAfn) with updates from Fall 2001 to Fall 2002 and back issues of Duncan's *American Radio* (Duncan, Spring 1996 to Spring 2001 when it ceased publication).

Arbitron ratings

Station shares of radio listening (AQH 12+) I use Arbitron 12+ AQH and APR data from Spring 1996 to Fall 2002. As BIAfn does not contain data on stations which exited prior to Fall 2001 shares for these stations were taken from back issues of Duncan's *American Radio*. Exit is relatively rare, and I only identified 20 such stations. I also used Duncan to fill in some gaps in the share data for stations which are listed in BIAfn. Most of these stations are based in Canada or Mexico but are rated in US markets such as Detroit or San Diego. I note that BIAfn's listing of a station's share does not include the share of stations which "simulcast" its signal on another frequency in the market. However, these shares are typically small.

Total Radio Listening (APR 12+) The proportion of the 12+ population listening to any radio station, listed or not, is not recorded by BIAfn. For Spring 1996 to Spring 2001 the APR numbers come from Duncan. There are a few missing numbers and no Small Market edition of Duncan for Spring 1996 so these market-quarters were dropped. For Fall 2001 to Fall 2002 there are no Duncan books so APR numbers were derived indirectly from M Street's STAR ratings database. STAR lists the number of persons aged 12 and above (12+) listening to a station in an average quarter hour (AQH Persons). The market APR can be derived from a station's AQH Share, its AQH Persons and the market's 12+ population (taken from Arbitron's website) through the following formula

$$\text{APR} = \frac{\text{AQH Persons}}{\text{12+ Population * AQH Share}}$$

I note that I cannot control for any changes in Arbitron market boundaries over the 1996 to 2002 period because I do not have data on these changes. However, Arbitron's website says that boundaries are "relatively static" and are primarily changed following the decennial census.

Station Categories

Station-quarter format information comes from BIAfn, with Duncan used for the added stations, some station-quarters where BIAfn had gaps and for a few cases where BIAfn lists the format as "Dark - Not on Air" even though the station has a positive listening share. These formats were categorized into 19 BIAfn categories using BIAfn's Fall 2001 classification. Duncan formats are not exactly the same as BIAfn formats but in practice including them in the classification was straightforward. For 231 station-quarters (mainly for Canadian and Mexican stations) both BIAfn and Duncan list formats as "N/A" or have missing entries. These station-quarters were categorized in an additional "Unknown" category.

Station Characteristics

The Fall 2001 version of the BIAfn database is the source of station characteristics data, apart from home metro-market information for the added stations which comes from Duncan. A few pieces of data on station start years and transmitter characteristics were missing and these were replaced in the regressions with dummies. I did not collect other characteristics data from Duncan because Duncan does not provide characteristic data for small stations.

Metro-Market Characteristics

Metro-market demographic and region characteristics come from the Fall 2001 BIAfn database (which takes them from the County Edition of Demographics USA, published by Market Statistics Inc.) apart from the commuting time data which comes from Arbitron's website and are derived from the 2000 census. For income I use Effective Buying Income per capita (defined as the average gross income less taxes). To create region dummies I use BIAfn's 9 region classification: East North Central, East South Central, Mid Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central and West South Central.

Station Ownership

I use BIAfn's transaction history for each station. For each transaction it lists the buyer, seller and date (month-year) and whether the deal was completed. A closing date is given for the most recent transaction for each station but for earlier transactions I only have the announcement date. Ownership data for the added stations comes from Duncan and none of them were traded before they exited. I note 4 issues with the ownership data. First, occasionally an owner's name can be presented differently for different stations. Considerable effort was expended trying to make sure that stations owned by the same owner were treated as such and those belonging to separate owners were not by checking the names of directors, notes included in the transaction history and transaction records at the front of Duncan publications. However, in some cases the situation was still unclear and I treated these stations as independents. Second, in 5% of cases BIAfn lists the parent as different from the station's owner. For example, this can happen if a large company has a stake in a station and has an option to buy the rest. There is no parent transaction history but the results are not sensitive to replacing the current owner with the current parent. Third, there are almost no transactions recorded for Canadian and Mexican stations. It is not clear whether this is correct. The results are not affected by dropping markets such as San Diego in which Canadian or Mexican stations are rated. Finally, my treatment of ownership ignores the existence of LMAs between stations in which one station owner, typically a group, sells advertising time on another station, typically a small independent, without actually owning it. LMAs may or may not influence other aspects of programming.

Table 3.1: Categories and Formats

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

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

Table 3.2: Coverage of the Airplay Sample
Based on Fall 2001 Categories and Station Ratings

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

Notes:

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

Table 3.3: Summary Statistics on the Structure of the Airplay Panel

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

Notes:

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

Table 3.4: Variety Analysis Summary Statistics

(a) Distance Measures

	Number of station-pair weeks	DISTANCE MEASURE 1 Each Artist Separate Dimension Mean	Std Dev	Min	Max	DISTANCE MEASURE 2 Each Artist-Song Separate Dimension Mean	Std Dev	Min	Max	DISTANCE MEASURE 3 Stations Located in 2-Dimensional Space Mean	Std Dev	Min	Max
Pairs Distances by Category													
Adult Contemporary (AC)	783,320	1.078	0.314	0.134	1.571	1.247	0.225	0.112	1.571	0.645	0.424	0.000	1.940
Album Oriented Rock/Classic Rock (AOR)	270,579	0.993	0.312	0.292	1.571	1.295	0.191	0.555	1.571	0.631	0.398	0.001	1.891
Contemporary Hit Radio (CHR)	425,893	1.023	0.279	0.317	1.571	1.104	0.260	0.387	1.571	0.562	0.384	0.001	1.881
Country	425,485	0.514	0.212	0.165	1.571	0.870	0.205	0.349	1.571	0.136	0.251	0.000	1.886
Oldies	13,502	0.881	0.432	0.230	1.571	1.170	0.281	0.411	1.571	0.499	0.526	0.001	2.460
Rock	361,947	1.143	0.314	0.248	1.571	1.278	0.239	0.408	1.571	0.779	0.444	0.001	2.055
Urban	175,753	1.068	0.276	0.235	1.571	1.175	0.242	0.283	1.571	0.601	0.394	0.001	1.926
Pairs in Same Format and Category													
Adult Contemporary (AC)	196,223	0.953	0.291	0.134	1.571	1.156	0.214	0.112	1.571	0.467	0.366	0.000	1.868
Album Oriented Rock/Classic Rock (AOR)	136,462	0.851	0.256	0.292	1.571	1.201	0.175	0.555	1.571	0.438	0.310	0.001	1.891
Contemporary Hit Radio (CHR)	269,761	1.006	0.267	0.317	1.571	1.088	0.252	0.387	1.571	0.543	0.369	0.001	1.808
Country	425,485	0.514	0.212	0.165	1.571	0.870	0.205	0.349	1.571	0.136	0.251	0.000	1.886
Oldies	11,101	0.755	0.367	0.230	1.571	1.091	0.246	0.410	1.571	0.356	0.456	0.001	2.460
Rock	86,580	0.908	0.269	0.248	1.571	1.123	0.217	0.422	1.571	0.450	0.327	0.001	1.721
Urban	65,912	0.972	0.247	0.235	1.571	1.094	0.219	0.283	1.571	0.466	0.336	0.001	1.722
MMC Average Distances	**Number of MMC-weeks**												
(all categories)	8,942	1.125	0.340	0.194	1.571	1.264	0.256	0.460	1.571	0.786	0.398	0.002	1.784
Distances from Category Centre	**Number of station-weeks**												
(all categories)	35,750	0.720	0.280	0.160	1.568	0.894	0.246	0.304	1.569	0.420	0.270	0.000	1.693

(b) Explanatory Variables

		Type	Mean	Std Dev	Min	Max
Pair Distances	**Number of pairs**					
SAME_REGION	2,456,479	Dummy	0.1289	-	0	1
SAME_MARKET	2,456,479	Dummy	0.0064	-	0	1
SAME_OWNER	2,456,479	Dummy	0.0999	-	0	1
SAME_MKTOWNER	2,456,479	Dummy	0.0015	-	0	1
MMC Average Distances	**Number of MMC-weeks**					
MEAN_SAME_MKTOWNER	8,942	0 to 1	0.2522	0.3931	0	1
ANY_SAME_MKTOWNER	8,942	Dummy	0.3675	-	0	1
Distances from Category Centre	**Number of station-weeks**					
ANOTHER_IN_MMC	35,750	Dummy	0.824	-	0	1
NUMBER_OWNED_IN_MMC	35,750	Number	1.371	0.603	1	4

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

Table 3.5: Variety Results: Pair Distance Regressions with No Category-Pair Dummies

	(1) Measure 1 Artist Dimensions	(2) Measure 2 Artist-Song Dimensions	(3) Measure 3 Artists in 2D Space	(4) Measure 1 Artist Dimensions	(5) Measure 2 Artist-Song Dimensions	(6) Measure 3 Artists in 2D Space	(7) Measure 1 Artist Dimensions	(8) Measure 2 Artist-Song Dimensions	(9) Measure 3 Artists in 2D Space	(10) Measure 1 Artist Dimensions	(11) Measure 2 Artist-Song Dimensions	(12) Measure 3 Artists in 2D Space
SAME_REGION	-0.021 (0.007) [0.032]	-0.017 (0.006) [0.039]	-0.019 (0.012) [0.171]	-0.021 (0.007) [0.032]	-0.017 (0.006) [0.039]	-0.019 (0.011) [0.171]	-0.010 (0.003) [0.020]	-0.008 (0.003) [0.034]	-0.005 (0.005) [0.339]	-	-	-
SAME_MARKET	0.141 (0.016) [0.000]	0.102 (0.013) [0.000]	0.196 (0.026) [0.000]	0.135 (0.019) [0.000]	0.094 (0.014) [0.001]	0.199 (0.025) [0.000]	0.078 (0.010) [0.000]	0.050 (0.007) [0.000]	0.123 (0.015) [0.000]	0.142 (0.009) [0.000]	0.102 (0.007) [0.000]	0.198 (0.014) [0.000]
SAME_OWNER	-0.038 (0.016) [0.051]	-0.032 (0.017) [0.106]	-0.041 (0.021) [0.098]	-0.038 (0.016) [0.051]	-0.032 (0.017) [0.106]	-0.041 (0.021) [0.098]	-0.010 (0.014) [0.530]	-0.003 (0.010) [0.775]	-0.008 (0.020) [0.696]	-0.048 (0.012) [0.000]	-0.042 (0.012) [0.001]	-0.046 (0.013) [0.001]
SAME_MKTOWNER	0.163 (0.029) [0.001]	0.098 (0.023) [0.005]	0.222 (0.037) [0.001]	0.169 (0.029) [0.001]	0.106 (0.020) [0.002]	0.219 (0.034) [0.001]	0.081 (0.023) [0.014]	0.041 (0.008) [0.002]	0.096 (0.028) [0.014]	0.173 (0.019) [0.000]	0.108 (0.014) [0.000]	0.223 (0.026) [0.000]
ONE_MKTOWNER	-	-	-	0.012 (0.021) [0.579]	0.016 (0.0176) [0.376]	-0.006 (0.024) [0.821]	-	-	-	-	-	-
Interactions with *SAME_FORMAT*												
SAME_REGION	-	-	-	-	-	-	-0.012 (0.010) [0.272]	-0.011 (0.010) [0.324]	-0.013 (0.018) [0.510]	-	-	-
SAME_MARKET	-	-	-	-	-	-	0.053 (0.025) [0.081]	0.043 (0.017) [0.044]	0.040 (0.033) [0.270]	-	-	-
SAME_OWNER	-	-	-	-	-	-	-0.040 (0.012) [0.016]	-0.045 (0.008) [0.001]	-0.045 (0.019) [0.058]	-	-	-
SAME_MKTOWNER	-	-	-	-	-	-	0.079 (0.093) [0.430]	0.053 (0.075) [0.508]	0.134 (0.123) [0.318]	-	-	-
Dummies	Week Category	Week Category	Week Category	Week Category	Week Category	Week Category	Week Format of Pair	Week Format of Pair	Week Format of Pair	Week Category	Week Category	Week Category
Adjusted R^2 (includes dummies)	0.3588	0.3383	0.2156	0.3588	0.3383	0.2156	0.5369	0.5003	0.4435	0.3543	0.3397	0.2168
Number of observations	2,456,479	2,456,479	2,456,145	2,456,479	2,456,479	2,456,145	2,456,479	2,456,479	2,456,145	316,631	316,631	316,578

Notes: Columns 1-9: standard errors in parentheses robust to heteroskedasticity and clustered at the music category level; p-values in square brackets calculated assuming t-statistics are distributed t with degrees of freedom equal to the number of categories/categories/clusters minus 1. Columns 10-12 standard errors clustered at the category-region level with t-statistics distributed normally.

Table 3.6: Variety Results: Pair Distance Regressions with Category-Pair Dummies (Fixed Effects)

	(1) Measure 1 Artist Dimensions	(2) Measure 2 Artist-Song Dimensions	(3) Measure 3 Artists in 2D Space	(4) Measure 1 Artist Dimensions	(5) Measure 2 Artist-Song Dimensions	(6) Measure 3 Artists in 2D Space	(7) Measure 1 Artist Dimensions	(8) Measure 2 Artist-Song Dimensions	(9) Measure 3 Artists in 2D Space	(10) Measure 1 Artist Dimensions	(11) Measure 2 Artist-Song Dimensions	(12) Measure 3 Artists in 2D Space
SAME_OWNER	-0.010 (0.007) [0.188]	-0.011 (0.006) [0.122]	-0.011 (0.006) [0.135]	-0.010 (0.007) [0.188]	-0.011 (0.006) [0.121]	-0.011 (0.006) [0.135]	-0.004 (0.004) [0.263]	0.001 (0.004) [0.775]	-0.009 (0.003) [0.034]	-0.014 (0.006) [0.026]	-0.017 (0.007) [0.008]	-0.010 (0.006) [0.138]
SAME_MKTOWNER	0.097 (0.028) [0.013]	0.064 (0.032) [0.091]	0.119 (0.033) [0.011]	0.096 (0.029) [0.018]	0.070 (0.035) [0.093]	0.125 (0.032) [0.008]	0.083 (0.022) [0.010]	0.059 (0.030) [0.099]	0.122 (0.040) [0.021]	0.101 (0.024) [0.000]	0.071 (0.027) [0.008]	0.117 (0.034) [0.000]
ONE_MKTOWNER	-	-	-	-0.002 (0.019) [0.937]	0.011 (0.022) [0.639]	0.012 (0.022) [0.614]	-	-	-	-	-	-
Interactions with *SAME_FORMAT*												
SAME_OWNER	-	-	-	-	-	-	-0.012 (0.013) [0.379]	-0.025 (0.004) [0.001]	-0.007 (0.008) [0.462]	-	-	-
SAME_MKTOWNER	-	-	-	-	-	-	0.024 (0.034) [0.506]	-0.000 (0.037) [0.992]	-0.015 (0.038) [0.703]	-	-	-
Dummies	Week Category-Pair	Week Category-Pair	Week Category-Pair	Week Category-Pair	Week Category-Pair	Week Category-Pair	Week Category-Pair Format of Pair	Week Category-Pair Format of Pair	Week Category-Pair Format of Pair	Week Category-Pair	Week Category-Pair	Week Category-Pair
Adjusted R^2 (includes dummies)	0.9317	0.8955	0.9315	0.9317	0.8955	0.9315	0.9308	0.8955	0.9295	0.9329	0.8977	0.933
Number of observations	1,548,039	1,548,039	1,547,823	1,548,039	1,548,039	1,547,823	801,751	801,751	801,606	316,631	316,631	316,578
Number of changes in *SAME_OWNER*	7,385	7,385	7,385	7,385	7,385	7,385	7,385	7,385	7,385	1,010	1,010	1,010
Number of changes in *SAME_MKTOWNER*	46	46	46	46	46	46	46	46	46	46	46	46

Notes:

1. Columns 1-9: standard errors in parentheses robust to heteroskedasticity and clustered at the music category level; p-values in square brackets calculated assuming t-statistics are distributed t with degrees of freedom equal to the number of categories/clusters minus 1.

2. Regressions done on a sample of category-pair distances. Sample for columns (1)-(6) contains all category-pairs which are in the same region or are ever commonly owned plus a 50% random sample of remaining pairs. Sample for columns (7)-(9) contains all category-pairs which are in the same region or are ever commonly owned plus a 10% random sample of other pairs. Random sample selected by allocating a random number between 0 and 1 to each category-pair and then using all pairs with a number above 0.5 or 0.9.

Table 3.7: Example Illustrating how Playlist Changes Affect Station Locations and Pair Distances

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

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

Table 3.8: Variety Results: Pair Distance Regressions Robustness Checks

(a) Regressions with No Category-Pair Dummies

	Measure 1: Each Artist as a Dimension of Product Space				Measure 3: Artists and Stations in 2D Product Space			
	SAME_REGION	*SAME_MARKET*	*SAME_OWNER*	*SAME_MKTOWNER*	*SAME_REGION*	*SAME_MARKET*	*SAME_OWNER*	*SAME_MKTOWNER*
Original coefficients	-0.021 (0.007) [0.032]	0.141 (0.016) [0.000]	-0.038 (0.016) [0.051]	0.163 (0.029) [0.001]	-0.019 (0.012) [0.171]	0.196 (0.026) [0.000]	-0.041 (0.021) [0.098]	0.222 (0.037) [0.001]
Robustness Check								
1. Use only pair-weeks where each station has at least 1,000 plays	-0.021 (0.008) [0.036]	0.133 (0.021) [0.001]	-0.036 (0.015) [0.057]	0.178 (0.030) [0.001]	-0.019 (0.013) [0.179]	0.178 (0.029) [0.001]	-0.041 (0.022) [0.105]	0.240 (0.036) [0.001]
2. Use only pair-weeks where each station has all possible days	-0.020 (0.007) [0.036]	0.137 (0.019) [0.000]	-0.035 (0.014) [0.046]	0.162 (0.028) [0.001]	-0.018 (0.012) [0.189]	0.192 (0.029) [0.001]	-0.038 (0.019) [0.095]	0.219 (0.036) [0.001]
3. *SAME_MARKET=1* if stations both have listening in any market	-0.014 (0.007) [0.071]	0.025 (0.011) [0.058]	-0.036 (0.016) [0.063]	0.115 (0.023) [0.003]	-0.010 (0.011) [0.378]	0.044 (0.018) [0.045]	-0.039 (0.021) [0.119]	0.150 (0.047) [0.018]
4. Week dummies interacted with *SAME_MARKET* dummy	-0.021 (0.007) [0.032]	-	-0.038 (0.016) [0.051]	0.164 (0.029) [0.001]	-0.019 (0.012) [0.171]	-	-0.041 (0.021) [0.099]	0.222 (0.037) [0.001]
5. Include dummies for the number of stations in each MMC	-0.023 (0.008) [0.027]	-	-0.059 (0.020) [0.025]	0.184 (0.017) [0.000]	-0.023 (0.012) [0.104]		-0.065 (0.024) [0.037]	0.245 (0.026) [0.000]
6. Use observations with at least 3 stations in each MMC	-0.012 (0.005) [0.055]	0.098 (0.008) [0.000]	-0.023 (0.018) [0.235]	0.137 (0.023) [0.001]	-0.008 (0.006) [0.211]	0.143 (0.014) [0.000]	-0.023 (0.019) [0.272]	0.192 (0.034) [0.001]
7. Use observations with only 1 station in each MMC	-0.044 (0.014) [0.020]	-	-0.043 (0.018) [0.053]	-	-0.050 (0.027) [0.107]	-	-0.055 (0.019) [0.027]	-
8. Each station appears in only one category-pair	-0.015 (0.049) [0.764]	0.178 (0.051) [0.001]	-0.033 (0.026) [0.214]	0.163 (0.039) [0.000]	0.004 (0.056) [0.943]	0.247 (0.060) [0.000]	-0.030 (0.032) [0.353]	0.236 (0.051) [0.000]

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

	Measure 1: Each Artist as a Dimension of Product Space				Measure 3: Artists and Stations in 2D Product Space			
	SAME_REGION	*SAME_MARKET*	*SAME_OWNER*	*SAME_MKTOWNER*	*SAME_REGION*	*SAME_MARKET*	*SAME_OWNER*	*SAME_MKTOWNER*
Original coefficients	-	-	-0.010 (0.007) [0.188]	0.097 (0.028) [0.013]	-	-	-0.011 (0.006) [0.135]	0.119 (0.033) [0.011]
Robustness Check								
1. Use only pair-weeks where each station has at least 1,000 plays	-	-	-0.006 (0.005) [0.305]	0.117 (0.024) [0.003]	-	-	-0.005 (0.005) [0.310]	0.131 (0.025) [0.002]
2. Use only pair-weeks where each station has all possible days	-	-	-0.010 (0.007) [0.169]	0.095 (0.028) [0.014]	-	-	-0.012 (0.006) [0.111]	0.115 (0.032) [0.011]
3. *SAME_MARKET=1* if stations both have listening in any market	-	-	-0.010 (0.007) [0.197]	0.020 (0.018) [0.308]	-	-	-0.011 (0.006) [0.142]	0.031 (0.028) [0.297]
4. Week dummies interacted with *SAME_MARKET* dummy	-	-	-0.010 (0.007) [0.190]	0.092 (0.026) [0.012]	-	-	-0.011 (0.006) [0.137]	0.115 (0.032) [0.011]
5. Include dummies for the number of stations in each MMC	-	-	-0.010 (0.007) [0.183]	0.098 (0.028) [0.012]	-	-	-0.011 (0.007) [0.140]	0.121 (0.032) [0.010]
6. Use observations with at least 3 stations in each MMC	-	-	-0.005 (0.006) [0.434]	0.103 (0.036) [0.030]	-	-	-0.005 (0.003) [0.194]	0.134 (0.052) [0.043]
7. Use observation with only 1 station in each MMC	-	-	-0.019 (0.006) [0.020]	-	-	-	-0.012 (0.010) [0.282]	-
8. Each station appears in only one category-pair	-	-	-0.013 (0.012) [0.295]	0.103 (0.033) [0.002]	-	-	-0.007 (0.014) [0.580]	0.109 (0.042) [0.010]

Notes: 1. Checks 1-7: standard errors in parentheses robust to heteroskedasticity and clustered at the music category level; p-values in square brackets calculated assuming t-statistics are distributed t with degrees of 'freedom equal tc the number of categories/clusters minus 1
2. Check 8 uses a sub-sample of the data in which each station appears only once in a pair in a category, so that there are 13,040 observations. The sub-sample was selected by the following procedure. First take the set of category-pairs which are home to the same MMC and which change whether they are commonly owned. If a station appears in more than one of these pairs, randomly select a single category-pair to keep for the sub-sample. I then drop (from the entire sample) any category-pair containing a station which has been put in the sub-sample in the same category. I then repeat this procedure for the set of remaining category-pairs which are home to the same MMC and are always commonly owned while they are in the data, and then (in order) category-pairs home to the same MMC which are never commonly owned, category-pairs home to different markets which change whether they are commonly owned and category-pairs home to different markets which are always commonly owned and then all remaining pairs. In this sub-sample 143 (32) pairs are home to the same MMC and (change whether they) are commonly owned and 166 (94) are home to different MMCs and (change whether they) are commonly owned. The standard errors are clustered at the level of the category-pair and the p-values assume that the t-statistics are distributed asymptotically normally.

Table 3.9: Variety Results: Alternative Specifications

(a) Metro-Market Category Average Distances

Explanatory Variables Used In Separate Regressions	(1) Measure 1 Each Artist as a Dimension	(2) Measure 2 Each Artist-Song as a Dimension	(3) Measure 3 Artist and Stations in 2D space	(4) Measure 1 Each Artist as a Dimension	(5) Measure 2 Each Artist-Song as a Dimension	(6) Measure 3 Artist and Stations in 2D space	(7) Measure 1 Each Artist as a Dimension	(8) Measure 2 Each Artist-Song as a Dimension	(9) Measure 3 Artist and Stations in 2D space
MEAN_SAME_MKTOWNER	0.140 (0.026) ***	0.073 (0.020) ***	0.187 (0.037) ***	0.052 (0.023) **	0.016 (0.029)	0.067 (0.031) **	0.046 (0.023) **	0.019 (0.028)	0.061 (0.030) **
ANY_SAME_MKTOWNER	0.109 (0.022) ***	0.055 (0.017) ***	0.149 (0.031) ***	0.043 (0.021) **	0.013 (0.027)	0.065 (0.030) **	0.039 (0.021) *	0.015 (0.026)	0.060 (0.029) **
Dummies	Week Category*Number of Stations in MMC Category*Number of Stations in MMC with Airplay Data	Week Category*Number of Stations in MMC Category*Number of Stations in MMC with Airplay Data	Week Category*Number of Stations in MMC Category*Number of Stations in MMC with Airplay Data	Week Identity of Stations in MMC	Week Identity of Stations in MMC	Week Identity of Stations in MMC	Week Identity of Stations Category*Number of Stations in MMC	Week Identity of Stations Category*Number of Stations in MMC	Week Identity of Stations Category*Number of Stations in MMC
Adjusted R^2 for *MEAN* regression (includes dummies)	0.5956	0.5670	0.4817	0.9325	0.8996	0.9243	0.9330	0.8996	0.9249
Number of observations	8,942	8,942	8,938	8,942	8,942	8,938	8,942	8,942	8,938

(b) Station Distance from Centre of Category

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

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

Table 3.10: Listenership Analysis Summary Statistics

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

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

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

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

Table 3.10: Listenership Analysis Summary Statistics cont.
(b) Nested Logit Model of Station Listenership

	Number of station-market-quarters	Mean	Standard Deviation	Min	Max
Listenership Shares					
s_{smt}	94,770	0.005	0.005	0	0.058
s_{omt}	94,770	0.870	0.015	0.799	0.935
$s_{c,smt}$	94,770	0.121	0.089	0.001	0.743
$s_{in,csmt}$	94,770	0.439	0.345	0.003	1
Ownership Variables					
DUM_OWNER_MKT (dummy)	94,770	0.721	-	0	1
DUM_OWNER_MMC (dummy)	94,770	0.223	-	0	1
OWNER_MARKET (station count)	94,770	3.484	2.485	1	17
OWNER_CATEGORY (station count)	94,770	14.059	27.070	1	144
Station Characteristics (Fall 2001 only)	**Number of station-markets**				
AGE (years plus 1)	7,075	40	20	2	94
AM_DAYMW (AM daytime transmitter power, kW/1000)	1,858	0.016	0.020	0.000	0.100
AM_NIGHTMW (AM nighttime transmitter power, kW/1000)	1,720	0.013	0.020	0.000	0.150
FM (dummy, 1 if station FM)	7,095	0.738	-	0	1
FM_HAAT (FM transmitter height, feet/1000)	5,230	0.908	0.905	-0.289	48.632
FM_MW (FM transmitter power, kw/1000)	5,235	0.043	0.041	0.000	0.320
OUT_AM (dummy, 1 if station AM and not home to market)	7,095	0.066	-	0	1
OUT_METRO (dummy, 1 if station not home to market)	7,095	0.351	-	0	1
Metro-Market Characteristics (Fall 2001 only)	**Number of markets**				
INCOME ($000 per capita post tax)	281	17.683	3.593	8.845	36.436
ASIAN (proportion)	281	0.028	0.048	0.004	0.674
BLACK (proportion)	281	0.113	0.106	0.003	0.517
HISPANIC (proportion)	281	0.093	0.136	0.005	0.943
POP_OVER65 (proportion aged over 65)	281	0.127	0.033	0.036	0.332
POP_UNDER18 (proportion aged under 18)	281	0.257	0.029	0.171	0.373
POP_18TO24 (proportion aged 18 to 24)	281	0.098	0.030	0.048	0.284
COMMUTETIME (average commute time in minutes)	281	22.711	3.851	15.100	38.300

Notes: Market characteristics statistics based on one observation per market. Station characteristics based on one observation per station-market in Fall 2001. FM_HAAT and FM_MW only calculated for FM stations, and AM_DAYMW and AM_NIGHTMW for AM stations. Additional dummies are included to indicate stations which have a particular characteristic missing or, for example, AM stations which do not operate at night.

Table 3.11: Listenership of Pairs in the Same Metro-Market Category (MMC)

(a) Pair Listenership and Common Ownership with No Category-Pair Dummies

Dependent Variable	(1) Pair *SHARE_LISTENING*	(2) Pair *LN(SHARE_LISTENING)*	(3) Pair *SHARE_12+*	(4) Pair *LN(SHARE_12+)*
SAME_MKTOWNER	0.0095 (0.0028)***	0.1151 (0.0322)***	0.0014 (0.0004)***	0.1108 (0.0618)***
Dummies	Ratings Quarter Category	Ratings Quarter Category	Ratings Quarter Category	Ratings Quarter Category
Adjusted R^2 (includes dummies)	0.1746	0.2015	0.2006	0.2294
Number of observations	4,714	4,714	3,014	3,014

(b) Pair Listenership and Common Ownership with Category-Pair Dummies (Fixed Effects)

Dependent Variable	(1) Pair *SHARE_LISTENING*	(2) Pair *LN(SHARE_LISTENING)*	(3) Pair *SHARE_12+*	(4) Pair *LN(SHARE_12+)*
SAME_MKTOWNER	0.0025 (0.0017)	0.0272 (0.0172)	0.0004 (0.0003)	0.0334 (0.0175)*
Dummies	Ratings Quarter Category-Pair	Ratings Quarter Category-Pair	Ratings Quarter Category-Pair	Ratings Quarter Category-Pair
Adjusted R^2 (includes dummies)	0.9116	0.9200	0.9116	0.9093
Number of observations	4,714	4,714	3,014	3,014
Number of changes in *SAME_MKTOWNER*	35	35	34	34

(c) Pair Listenership and Common Ownership Controlling for Changes in the Number of Stations in the MMC

Dependent Variable	(1) Pair *SHARE_LISTENING*	(2) Pair *LN(SHARE_LISTENING)*	(3) Pair *SHARE_12+*	(4) Pair *LN(SHARE_12+)*
SAME_MKTOWNER	0.0018 (0.0017)	0.0207 (0.0175)	0.0003 (0.0003)	0.0260 (0.0171)
Dummies	Ratings Quarter Category-Pair Number of Home Stations in MMC	Ratings Quarter Category-Pair Number of Home Stations in MMC	Ratings Quarter Category-Pair Number of Home Stations in MMC	Ratings Quarter Category-Pair Number of Home Stations in MMC
Adjusted R^2 (includes dummies)	0.9128	0.9213	0.895	0.9108
Number of observations	4,714	4,714	3,014	3,014
Number of changes in *SAME_MKTOWNER*	29	29	29	28

(d) Pairs Listenership and Common Ownership Controlling for the Identity of Stations in the MMC

Dependent Variable	(1) Pair *SHARE_LISTENING*	(2) Pair *LN(SHARE_LISTENING)*	(3) Pair *SHARE_12+*	(4) Pair *LN(SHARE_12+)*
SAME_MKTOWNER	0.0007 (0.0022)	0.0098 (0.0243)	0.0002 (0.0003)	0.0163 (0.0235)
Dummies	Ratings Quarter Category Pair Identity of Stations in MMC	Ratings Quarter Category Pair Identity of Stations in MMC	Ratings Quarter Category Pair Identity of Stations in MMC	Ratings Quarter Category Pair Identity of Stations in MMC
Adjusted R^2 (includes dummies)	0.9247	0.9307	0.9171	0.9230
Number of observations	4,714	4,714	3,014	3,014
Number of changes in *SAME_MKTOWNER*	20	20	20	20

Note: Standard errors in parentheses robust to heteroskedasticity and clustered at the MMC level; p-values in square brackets calculated assuming t-statistics are distributed t with degrees of freedom equal to the number of MMCs minus 1.

Table 3.12: Nested Logit Model of Listenership

(a) Substitution Patterns Estimated from Within-Market Variation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(s_{in,csmt})$, 1-δ	0.6540 (0.0265)***	0.6544 (0.0265)***	0.6526 (0.0268)***	0.6509 (0.0270)***	0.6519 (0.0269)***	0.6510 (0.0268)***	0.6523 (0.0266)***
$\ln(s_{c,smt})$, 1-δτ	0.6859 (0.0240)***	0.6860 (0.0241)***	0.6848 (0.0243)***	0.6834 (0.0244) ***	0.6843 (0.0244)***	0.6839 (0.0243)***	0.6844 (0.0242)***
DUM_OWNER_MKT	0.0081 (0.0030)***	-	-	-	-	0.0078 (0.0029)***	0.0068 (0.0030)**
LN(OWNER_MKT)	-	0.0047 (0.0022)**	-	-	-	-	-
DUM_OWNER_MMC	-0.0026 (0.0029)	-0.0025 (0.0029)	-0.0007 (0.0028)	-	0.0001 (0.0027)	-	-0.0029 (0.0031)
LN(OWNER_CATEGORY)	0.0007 (0.0010)	0.0003 (0.0011)	0.0011 (0.0010)	0.0010 (0.0010)	-	-	0.0007 (0.0011)
*AIRPLAY * DUM_OWNER_MKT*	-	-	-	-	-	-	0.0121 (0.0037)***
*AIRPLAY * DUM_OWNER_MMC*	-	-	-	-	-	-	0.0004 (0.0037)
*AIRPLAY * LN(OWNER_CATEGORY)*	-	-	-	-	-	-	-0.0012 (0.0011)
Dummies	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category
Number of observations	94,770	94,770	94,770	94,770	94,770	94,770	94,770

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DUM_OWNER_MKT	0.0038 (0.0015)**	-	-	-	-	0.0061 (0.0015)***	0.0035 (0.0016)**
LN(OWNER_MKT)	-	0.0016 (0.0011)	-	-	-	-	-
DUM_OWNER_MMC	0.0082 (0.0014)***	0.0085 (0.0014)***	0.0091 (0.0014)***	-	0.0090 (0.0013)***	-	0.0085 (0.0015) ***
LN(OWNER_CATEGORY)	-0.0003 (0.0005)	-0.0004 (0.0006)	-0.0001 (0.0006)	0.0007 (0.0005)	-	-	-0.0003 (0.0006)
*AIRPLAY * DUM_OWNER_MKT*	-	-	-	-	-	-	0.0029 (0.0019)
*AIRPLAY * DUM_OWNER_MMC*	-	-	-	-	-	-	-0.0013 (0.0019)
*AIRPLAY * LN(OWNER_CATEGORY)*	-	-	-	-	-	-	-0.0002 (0.0006)
Dummies	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category	Ratings Quarter Station-Market-Category
Number of observations	94,770	94,770	94,770	94,770	94,770	94,770	94,770

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

Table 3.12(b): Estimation of Nested Logit Model Substitution Patterns from Cross-Sectional Variation

	Fall 2001 only	**All ratings quarters, but Fall 2001 characteristics**
$\ln(s_{in,csmt})$, $1-\delta$	0.856 (0.009) ***	0.846 (0.007) ***
$\ln(s_{c,smt})$, $1-\delta\tau$	0.920 (0.005) ***	0.909 (0.004) ***
Market Characteristics		
INCOME	-0.002 (0.001)	-0.001 (0.001)
ASIAN	0.294 (0.069) ***	0.272 (0.070) ***
BLACK	0.109 (0.052) **	0.040 (0.044)
HISPANIC	0.245 (0.039) ***	0.224 (0.031) ***
POP_OVER65	-0.401 (0.204) **	0.117 (0.170)
POP_UNDER18	-0.231 (0.291)	0.209 (0.251)
POP_18TO24	-1.841 (0.258) ***	-1.258 (0.195) ***
COMMUTETIME	0.007 (0.002) ***	0.006 (0.001) ***
Station Characteristics		
FM	0.075 (0.010) ***	0.095 (0.008) ***
*AM*NEWS_TALK_SPORT*	0.003 (0.016)	0.027 (0.013) **
LN_AGE	0.018 (0.003) ***	0.026 (0.003) ***
OUT_METRO	-0.113 (0.006) ***	-0.133 (0.005) ***
*OUT_METRO*AM*	0.017 (0.009) *	0.024 (0.007) ***
FM_MW	0.435 (0.060) ***	0.481 (0.058) ***
AM_DAYMW	0.632 (0.276) **	0.718 (0.213) ***
AM_NIGHTMW	0.805 (0.302) ***	0.745 (0.250) ***
FM_HAAT	0.006 (0.004)	0.005 (0.005)
Quarter Dummies (Spring 1996 excluded)		
FALL_1996	-	-0.028 (0.001) ***
SPRING_1997	-	-0.023 (0.001) ***
FALL_1997	-	-0.051 (0.001) ***
SPRING_1998	-	-0.042 (0.002) ***
FALL_1998	-	-0.075 (0.002) ***
SPRING_1999	-	-0.072 (0.002) ***
FALL_1999	-	-0.111 (0.002) ***
SPRING_2000	-	-0.107 (0.002) ***
FALL_2000	-	-0.130 (0.002) ***
SPRING_2001	-	-0.126 (0.002) ***
FALL_2001	-	-0.183 (0.002) ***
SPRING_2002	-	-0.163 (0.002) ***
	-	-0.201 (0.002) ***
Dummies	Categories Regions Categories, Market Characteristic Interactions Category, Region Interactions Dummies for stations lacking different characteristics	Categories Regions Categories, Market Characteristic Interactions Category, Region Interactions Dummies for stations lacking different characteristics
Instruments for $\ln(s_{in,csmt})$, $1-\delta$ and $\ln(s_{c,smt})$, $1-\delta\tau$	Sum of Station Characteristics for other stations in Market-Category-Quarter Sum of Station Characteristics for Stations in other Categories in the same Market-Quarter	Sum of Station Characteristics for other stations in Market-Category-Quarter Sum of Station Characteristics for Stations in other Categories in the same Market-Quarter
Number of observations	7,095	94,770

Notes
1. Standard errors in parentheses, robust to heteroskedasticity and clustered on the identity of the station. For example, this allows for the errors for a station rated in two markets to be correlated. When I use all of the quarters this also allows for a station's errors to be correlated across quarters.
2. Estimation by 2SLS
3. ***, **, * indicate significant at 1,5,10% level respectively

Table 3.13: Does Product Differentiation Cause Listenership to Increase?

(a) Coefficient Estimates

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

<u>Note</u>

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

(b) Significance tests on linear combinations of coefficients

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

Table 3.A1: Results of Monte Carlo Simulation Exercise to Check Standard Errors in Pair Distance Regressions

(a) Measure 1 without Category-Pair Dummies

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

(b) Measure 3 without Category-Pair Dummies

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

(c) Measure 1 with Category-Pair Dummies

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

(d) Measure 3 with Category-Pair Dummies

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

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

Chapter 4

Coordination, Differentiation and the Timing of Radio Commercials

4.1 Introduction

Commercial radio stations tend to have commercials at the same time. For example, commercial breaks on any pair of stations in the same market between 4pm and 5pm overlap, on average, 33% more than they would if the stations had the same number of minutes of commercials during the hour but they were played randomly during the hour with any minute equally likely to be chosen.[1] However, this pattern could either be explained by stations wanting to choose the same time for commercial breaks as other stations in their market or by each station tending to find particular times in each hour more attractive for having commercial independent of when other stations decide to play their commercials. It is plausible that a station wants to play its commercials at the same time as other stations in its market because its primary business is to sell the audience of commercials to advertisers, who only value people listening to the commercials, and many listeners try to avoid commercials by looking for music being played simultaneously by other stations. If stations play commercials at the same time then the avoidance of commercials can be reduced.[2] However, the alternative explanation, that the

[1]Calculation based on a sample of 343,743 within-metro-market pairs of stations (an unbalanced panel of 1,076 stations from 133 markets on 119 days). The data is described in more detail in Section 3.

[2]The threat that listener switching to avoid commercials poses to the radio business model is understood within the industry. For example, Brydon (1994), an advertising consultant talking about the avoidance of

pattern reflects some times being more attractive for commercials independent of coordination, is consistent with the fact that very similar times have commercials in almost all metro-markets and music categories. Figure 4.1(a) shows the number of stations playing commercials in each minute between 4pm and 5pm across 147 different metro-markets while Figures 4.1(b)-(f) show the same histograms for three music categories (Album Oriented Rock/Classic Rock, Contemporary Hit Radio/Top 40 and Country) and two particular metro-markets, Chicago and Boston. In all of the diagrams the distributions have three peaks, with the quarter-hours having relatively few commercials and the second and fourth quarters tend to have the most commercials. These features can be explained without stations wanting to choose the same times as each other. First, Arbitron's methodology for estimating station ratings creates an incentive for stations not to play commercials on the quarter-hours so that they instead "sweep the quarter-hours" with music.[3] Second, more listeners are believed to first tune-in close to the hour or half-hour and they are believed to particularly dislike hearing commercials when they first tune-in. As a result, stations play fewer commercials in the first and third quarters of the hour.[4]

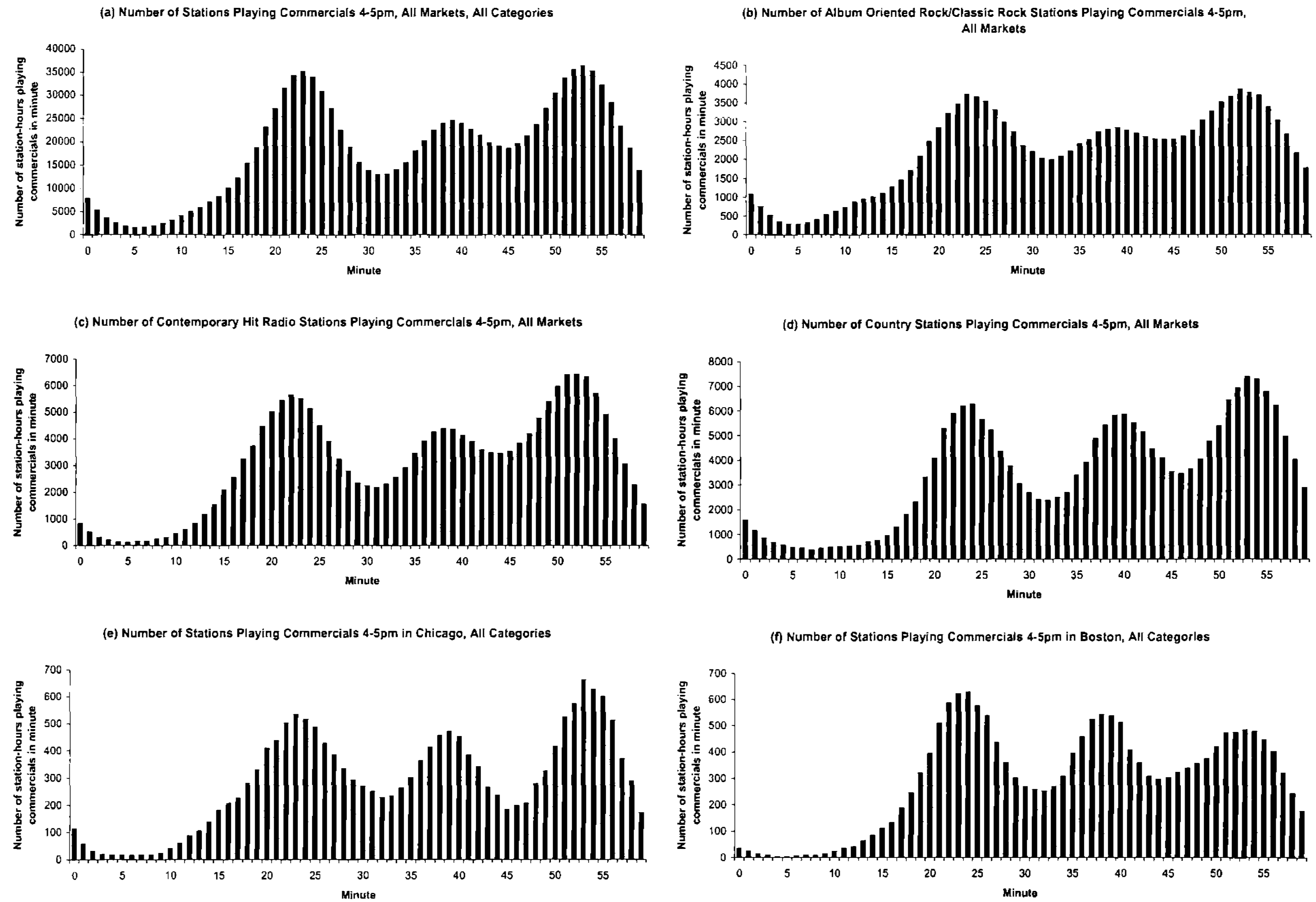
These competing explanations for the same observed aggregate patterns prompt the question of whether and how we can identify the role of strategic interactions between stations in determining stations' timing choices. There are 3 different possible approaches to this question. The first approach, used in Sweeting (2004a), is to assume that independent of any incentives to coordinate, the attractiveness of choosing a particular timing arrangement is the same across

commercials on music radio, states that "for advertisers, the key point is this: if, at the touch of a button, you can continue to listen to that for which you tuned in, why should you listen to something which is imposing itself upon you, namely a commercial break?". Brydon suggests two possible remedies: stations should have very short breaks or "transmit breaks at universally agreed, uniform times. Why tune to other stations if it's certain that they will be broadcasting commercials as well?"

[3]A listener counts as a quarter-hour listener for a station if she records herself as listening to the station for at least 5 minutes during the quarter-hour so that if she records that she listened from 4:10 to 4:20 she counts as a listener for both the 4:00-4:15 and the 4:15-4:30 quarter-hours. In order to keep as many listeners as possible most music stations "sweep" the quarter-hours with music which most listeners prefer to commercials (Warren (2001), p. 23-24).

[4]Ed Shane of Share Media (quoted in Keith (2000), p. 96) provides the following description: "[L]et me call what follows "Clock Construction 101". Arbitron entries show that the first quarter hour (:00-:15) gets the highest number of new entries, that is when the radio is tuned in for the first time or switched to a new station. The third quarter hour (:30-:45) gets the second largest number. The second quarter hour (:15-:30) gets the third largest number and the fourth quarter hour (:45-:00) gets the fewest new tune-ins. That is why many stations load their commercial content in the final or fourth quarter hour - trying to prevent a new listeners from hearing a commercial as the first thing when tuning."

Figure 4-1



Notes: (a) based on 94,509 station-hours, (b) 11,754 station-hours, (c) 16,919 station-hours, (d) 16,435 station-hours, (e) 1,418 station-hours, (f) 1,471 station-hours metro-markets, so that any clustering of commercials at slightly different times in different metro-markets, for example Los Angeles at 4:50pm and San Francisco at 4:55pm, can be used to identify the incentive to coordinate. The second approach, which is the subject of on-going research, is to assume that the attractiveness of particular parts of each hour, independent of what other stations choose, is the same across hours and then to use the fact that the most popular times are more likely to be chosen in the drivetime, when we know more listeners switch stations to avoid commercials, to identify the additional effect of coordination during drivetime. The third approach, which I use here, is to consider which market characteristics are likely to affect the equilibrium degree to which commercials overlap if there is strategic interaction on timing and then to test whether variation in these characteristics across markets is associated with significant differences in the observed degree of overlap. For example, suppose that each station wants to choose the same times for its commercials as other stations in its market to increase the number of people who listen to its commercials but that it can be costly to coordinate because it is hard to schedule commercials precisely around other kinds of programming, such as songs or phone-ins, which can vary or be somewhat unpredictable in length. If each station is independently owned and each station maximizes its own payoff then its optimal strategy will reflect a trade-off between its own benefits from coordinating with other stations and its own costs from trying to coordinate closely. Each station will ignore the fact that when it coordinates with other stations it also increases their audiences. However, when stations are commonly owned they should take these externalities into account which should increase the degree to which commercials overlap in equilibrium. Alternatively if stations want to play their commercials when other stations are not playing them, which can be rationalized by certain specifications of listener behavior, then we would expect more concentrated ownership to be associated with less overlap of commercials.

I present a simple model for examining the incentives of stations to coordinate on timing and show that whether stations want to coordinate (choose the same times for commercial breaks) or differentiate (choose different times for commercial breaks) on timing depends on the exact formulation of listener behavior. I illustrate the effects of changing the propensity of listeners to switch stations, the number of stations in the market and the degree of common ownership on equilibrium outcomes using 3 formulations of listener behavior. I then use a new panel dataset on the timing of radio commercials by 1,090 contemporary music radio stations in 147 different metro-markets to examine whether the data are consistent with the comparative statics suggested by the model and whether the evidence suggests that stations want, on average, to coordinate or differentiate on timing. I form measures of the degree to which commercials overlap, controlling for the quantity of commercials each station has and the music category of each station, among all of the music stations in a metro-market and among all of the stations in a metro-market and in the same music category. When I measure overlap at the metro-market level I find reasonably strong evidence that market characteristics affect the degree of coordination in a way consistent with a model where stations want to choose the same times for commercials. In particular there is less coordination in markets with many stations, in markets where there is a lot of listening to stations outside of the market and where there is less concentrated station ownership. These results are also slightly stronger during drivetime when a greater number of listeners can switch stations to avoid commercials. The evidence is weaker when I measure overlap at the metro-market-category level, although it is stronger when I drop observations from the largest 10 metro-markets. I also examine coordination between particular pairs of stations, where generally insignificant results suggest that commonly owned stations in the same music category coordinate less than separately owned stations.

There is a small related literature on the timing of commercial breaks. Epstein (1998), Zhou (2000) and Kadlec(2001) provide models of the timing of TV commercials within well-defined TV programs. In the Epstein and Zhou models stations choose to play commercials at the same time in equilibrium and this is also true in the Kadlec model for certain parameter values. I show that whether stations want to play commercials at the same or different times depends on the exact formulation of listener behavior. Epstein (1998) uses data on the timing of TV commercials by the major US networks during primetime to show that their commercials do tend to be broadcast at the same time even when the shows in which they are placed vary in length across channels. Studying the radio industry has the advantage that it is possible to study how the degree of overlap in timing depends on market characteristics which is not possible when analyzing the national TV networks. There is also a small literature on listener behavior in response to commercials. McDowell and Dick (2003) show that the avoidance of commercials is the main reason in-car listeners switch stations. Abernethy (1991) studied in-car switching using tape recorders placed in cars and found that on average in-car listeners switch more than 29 times during an hour, avoiding more than one half of the commercials they would hear if they did not switch stations. An industry study, by Arbitron and Edison Media Research (1999), found that 41% of listeners reported that they "never or rarely" change stations during commercials in their cars, compared with 61% and 67% at home and at work, suggesting that when more listeners are in their cars during drivetime, the average propensity of listeners to switch stations to avoid commercials should be higher. I use this fact to help test the comparative statics of the model.

Section 4.2 presents the simple model and describes the comparative statics under different formulations of listener behavior. Section 4.3 outlines the data and Section 4.4 describes the empirical specifications and the construction of the measures of overlap. Section 4.5 presents the empirical results. Section 4.6 concludes.

4.2 Simple Models of Station Timing Decisions and Listener Behavior

This section presents some simple models of station timing decisions which illustrate the kind of assumptions under which stations would want to coordinate or differentiate on the timing of commercials and the way in which a number of variables, in particular the propensity of listeners to switch stations, the number of stations in the market and the degree of common station ownership affect the degree of coordination in equilibrium. I show that whether stations want to coordinate or differentiate depends on the exact formulation of listeners' behavior, and while we know that many listeners do switch stations in response to commercials, there is no research which tells us directly which is the correct formulation.

4.2.1 Basic set-up

Suppose that time is divided into an infinite sequence of discrete intervals with alternate "even" and "odd" intervals. There are N (≥ 2) symmetric stations and N units of listeners. Each station is assumed to play commercial breaks in alternate intervals, so it must choose whether to play them in even or odd intervals. When stations are not playing commercials they play music which listeners prefer, at least on average, to commercials. A station i makes its choice to maximize its expected payoff. Payoffs from choosing even and odd have the following form:

$$\pi_{i,EVEN} = \beta + \alpha A_i^{EVEN}(\theta, N, n^{EVEN}) + \varepsilon_{i,EVEN} \tag{4.1}$$

$$\pi_{i,ODD} = A_i^{ODD}(\theta, N, n^{ODD}) + \varepsilon_{i,ODD} \tag{4.2}$$

β, assumed to be weakly greater than zero, allows even intervals to be more attractive for commercials, on average, independent of other stations' choices. For example, odd intervals might include the quarter-hour points which are less attractive because of Arbitron's rating methodology. $\varepsilon_{i,EVEN}$ and $\varepsilon_{i,ODD}$, assumed to be distributed Type I extreme value, give stations idiosyncratic preferences over timing arrangements and are independent across stations. They can be thought of as representing both differences in stations' preferences over scheduled arrangements for commercials (for example, one station may want to have news at the top of the hour preventing commercials from being played then) and noise in the implementation of scheduled arrangements due to the fact that some elements of programming, such as songs or phone-ins, can differ or be somewhat unpredictable in length. $A_i^{EVEN}(\theta, N, n^{EVEN})$ and $A_i^{ODD}(\theta, N, n^{ODD})$ are i's average audiences of its commercials when it plays them in even and odd periods respectively and n^{EVEN} other stations choose to play them in even. α parameterizes how important a station's audience is in station payoffs relative to β and the εs and θ is a parameter which indexes the propensity of listeners to switch stations to avoid commercials.[5]

Stations simultaneously choose when to play their commercials and the ε_is are assumed to be private information to station i so each station maximizes its expected payoff. Given the strategies of the other players, S_{-i}, i's optimal strategy will be to choose even if and only if

$$\varepsilon_{i,ODD} - \varepsilon_{i,EVEN} \leq \beta + \alpha E(A_i^{EVEN} - A_i^{ODD} | \theta, N, S_{-i}) \tag{4.3}$$

[5]It is an assumption that stations try to maximize the audience of their commercials, as advertisers would like them to, even though is not directly measured by Arbitron. This assumption is also made by Epstein (1998), Zhou (2000) and Kadlec (2001). Dick and McDowell (2003) show how the standard ratings numbers to which advertisers do have access can be used to estimate the relative amount of commercial avoidance on different stations.

so that i will be more likely to choose even when she expects a larger audience for commercials by choosing even rather than odd. i's optimal strategy can be conveniently expressed as a probability, p_i^*, of choosing "even" prior to the realization of its ε_is. Given the extreme value distribution of the ε_is,

$$p_i^* = \frac{e^{\beta + E(A_i^{EVEN} - A_i^{ODD} | \theta, N, S_{-i})}}{1 + e^{\beta + E(A_i^{EVEN} - A_i^{ODD} | \theta, N, S_{-i})}} \tag{4.4}$$

There is a Bayesian Nash equilibrium when each player is using her optimal strategy given the strategies of the other players.

I now present 3 alternative formulations of listener behavior. Formulations 1 and 2 lead to each station wanting, all else equal, to choose the same times for commercials as the majority of other stations in its market, while formulation 3 leads to each station wanting to choose different times to the majority of other stations.

Formulation 1. Every listener listens either to her first choice station or her second choice station. Each station is the first choice of one unit of listeners, and preferences are independent so that these listeners' second choices are equally divided between the $N-1$ other stations. There are two listener types which are distributed independently of station preferences. Proportion $1-\theta$ of listeners never switch stations and therefore always listen to their first choice station. The remaining proportion, θ, of listeners can switch stations and listen to their first choice unless it has commercials and their second choice plays music in which case they listen to their second choice. The audience for a commercial break on station i when N_{-i} other stations are playing commercials at the same time is simply

$$A_i = 1 - \theta + \theta \frac{N_{-i}}{N-1} \tag{4.5}$$

so, all else equal, a station increases the audience of its commercials by playing them at the same time as a greater proportion of other stations.

Formulation 2. Every listener has a first choice station with every other station considered to be perfect substitutes as a second choice. Each station is the first choice of one unit of listeners. There are two listener types distributed independently of station preferences. Proportion $1-\theta$ of listeners never switch stations and therefore listen to their first choice station independent of what it plays. The remaining proportion, θ, of listeners can switch stations and listen to their first choice unless it has commercials when any other station is playing music in which case they listen to one of the stations playing music. The audience of a commercial break on i when N_{-i} other stations are playing commercials at the same time is

$$A_i = 1 \text{ if } N_{-i} = N - 1 \text{ and } A_i = 1 - \theta \text{ if } N_{-i} < N - 1 \tag{4.6}$$

so a station only increases the audience of its commercials by playing it at the same time as every other station.

Formulation 3. Every listener has two equally favorite stations. Each station is a favorite of two units of listeners, and preferences are independent so that these listeners are equally divided between the $N - 1$ other stations for their other favorite station. Listeners also have an outside option (called NPR) which never has commercials. When a listener is listening to one of her favorite stations she continues to listen to it when it is playing music but when it plays commercials she switches with probability θ, to her other favorite station if it is playing music and otherwise to NPR in which case she switches back to one of her favorite stations (chosen randomly) for the next interval when they will both be playing music. The expected steady-state audience of a commercial break when N_{-i} other stations play commercials at the same time is

$$A_i = N_{-i}\left(\frac{1-\theta}{N-1}\right) + (N - N_{-i} - 1)\left(\frac{2}{2-\theta}\frac{1-\theta}{N-1}\right) \tag{4.7}$$

which decreases in N_{-i} for $\theta > 0$ so a station increases its audience by choosing a different time for commercials than other stations.[6] The difference from the previous formulations is that now the audience of a commercial break is proportional to the number of listeners the station has in the interval prior to the break. This is increased by playing music when most other stations have commercials.

[6]The formula in (4.7) is based on the expected steady-state audience of a commercial break: the average audience of a commercial break tend towards this value for any initial distribution of listeners between the stations.

4.2.2 Comparative Statics

I consider how the equilibrium degree of coordination/differentiation varies with θ, N and whether some of the stations are commonly owned, illustrating the effects with examples using the three formulations of listener behavior described above.

θ (the propensity of listeners to switch stations in response to commercials): under any of the formulations of listener behavior, $\frac{\partial |E(A_i^{EVEN} - A_i^{ODD}|\theta, N, S_{-i})|}{\partial \theta} \geq 0$, i.e., as more listeners switch the size of the audience during commercials is more sensitive to timing. It is clear from (4.3) that, as θ increases, a station has more incentive to want to choose the same times as other stations if this increases the audience of its commercials and more incentive to differentiate if this increases the audience of its commercials.

To illustrate this, suppose that $\beta = 0.7$ and $\alpha = 2$, with θ either 0 or $\frac{1}{2}$. Under formulation 1 or formulation 3 the symmetric equilibria are independent of the number of stations because the audience of a commercial break only depends on the proportion of other stations choosing each timing arrangement. With $\theta = 0$ stations choose even with probability 0.6682 (even is more attractive than odd because β is positive) under either formulation. Under formulation 1, it is easy to show that each station chooses even with probability 0.7784 in equilibrium if $\theta = \frac{1}{2}$ so, in expectation, a commercial break is more likely to overlap with those of other stations than if $\theta = 0$. On the other hand under formulation 3, even is chosen with probability 0.5824 in equilibrium if $\theta = \frac{1}{2}$ (assuming that the symmetric equilibrium is played) so, in expectation, a commercial break is less likely to overlap with those of other stations than if $\theta = 0$.

N (the number of stations): under formulations 1 and 3 the number of stations does not affect equilibrium strategies, at least when they are independently owned, but this is not true under the formulation 2 in which potential switchers only listen to commercials if all stations are playing commercials at the same time. For given strategies of other stations this becomes increasingly unlikely to happen as the number of stations increases, reducing the absolute value of $E(A_i^{EVEN} - A_i^{ODD}|\theta, N, S_{-i})$ and so thereby reducing the incentive of any station to try to coordinate. For example with $\beta = 0.7$, $\alpha = 2$, and $\theta = \frac{1}{2}$, it is easy to show that the equilibrium probability that a station chooses even is 0.7785, 0.7785, 0.7522, 0.7253 and 0.7052 for $N = 2, 3, 4, 5$ and 6 stations respectively, so that, in expectation, a commercial break is less likely to overlap with those of other stations as the number of stations increases. Note that as

θ increases the effect of the number of stations can become more pronounced.[7] For example if $\theta = \frac{2}{3}$ the equilibrium choice probabilities would be 0.8287, 0.8287, 0.7959, 0.7560 and 0.7236 for $N = 2, 3, 4, 5$ and 6 respectively.

Common ownership of stations: when a station is commonly owned with other stations in its market it has more incentive to want to coordinate with them if this increases the audience of their commercials as well as its own. To be precise, suppose that station i is commonly owned with station j and that while i is not able to observe the ε_js when deciding the timing of its commercials, it takes into account how its timing decision affects the expected audience of j's commercials.[8] In this case, i chooses even if and only if

$$\varepsilon_{i,ODD}-\varepsilon_{i,EVEN} \leq \beta+\alpha E(A_i^{EVEN}-A_i^{ODD}|\theta, N, S_{-i})+\alpha E(A_j^{i,EVEN}-A_j^{i,ODD}|\theta, N, S_{-i}) \quad (4.8)$$

where $E(A_j^{i,EVEN} - A_j^{i,ODD}|\theta, N, S_{-i})$ is the expected difference between the average audience of j's commercials when i chooses even and the average audience of j's commercials when i chooses odd, given the strategies of the other stations, including j. The internalization of the externality leads to more coordination by the commonly owned stations if they want to choose the same times for commercials. This also leads the non-commonly owned stations to coordinate more because coordination is a strategic complement (Bulow et al. (1985)). For example, under formulation 1 suppose that $\beta = 0.7$, $\alpha = 2$, $\theta = \frac{1}{2}$, $N = 4$. If the stations are all owned by independents then in the unique equilibrium each station chooses even with probability 0.7785. On the other hand if two stations are commonly owned and the rest are owned by separate independents then in the unique equilibrium each of the commonly owned stations chooses even with probability 0.8192 and the independents choose even with probability 0.7889. Note that as θ increases the effect of common ownership can also become greater. For example, if $\theta = \frac{2}{3}$ the equilibrium choice probabilities for the commonly owned stations and the independents would be 0.8790, 0.8790 and 0.8427 compared with 0.8287 with only independent

[7] In note that the effect of a change in N does not have to become more pronounced as θ increases. In particular, equilibria can be very coordinated for a large range of N if θ is very large whereas with moderate values of θ equilibria can be less coordinated and equilibrium strategies can more sensitive to the number of stations.

[8] If common ownership allows i and j to see each others' εs before deciding on their timing then they would tend to become even more coordinated with common ownership.

ownership.

Of course there are several aspects of the timing game, not least each station's decision over the quantity of commercials to play and the effect of asymmetries between stations, which have not been modelled at all here. In Section 4.5 I control, for example, for asymmetries in station listenership. If these do affect equilibrium strategies then it is also sensible to expect them to have more effect on coordination when listeners have a higher propensity to switch stations (θ high).

4.2.3 Summary of comparative static predictions

In Section 4.5 I use data on station timing decisions to form measures of the degree to which commercials on stations in a market overlap and I regress these measures on characteristics such as the number of stations in the market, the proportion of rated listening which is to stations outside the market, the degree of common ownership and the average quantity of commercials. The regressions are designed to test the extent to which the data are consistent with the comparative statics in the above models. For example, if stations want to choose the same times for commercial breaks we would expect common ownership not only to matter, in the sense of being statistically significant, but also greater common ownership to be associated with a higher degree of overlap of commercials. Similarly, if we assume that more stations tend to make coordination harder, then we would expect a larger number of stations to be associated with less coordination. On the other hand, if stations want to choose different times for commercial breaks we would expect less common ownership or a larger number of stations to be associated with a higher degree of overlap.

I estimate the regressions for 3 different dayparts: drivetime (6:00am-9:59am & 3:00pm-6:59pm), daytime (10am-2:59pm) and night (7pm-5:59am). The first two match weekday dayparts defined by Arbitron as grouping hours with similar listening patterns. The night hours combine Arbitron's 7pm-midnight and midnight-6am dayparts. An important feature of drivetime is that there are more in-car listeners than during other periods of the day and, as described in the introduction, in-car listeners are particularly likely to switch stations in response to commercials.[9] If the degree of overlap reflects an equilibrium outcome to a timing game

[9] For example, in Fall 2001, an average 39.2% of listening was in-car during weekday drivetimes compared

between the stations I therefore expect that characteristics which affect equilibrium overlap, such as the number of stations, may have larger and more significant effects on overlap during drivetime than outside drivetime.

4.3 Data

I create a new dataset on the timing of commercials using daily airplay logs collected by Mediabase 24/7, which uses electronic voice recognition technology to collect data on music airplay. The logs contain information on the timing of commercials for a significant number of stations during 2000 and 2001. I have daily airplay logs from the first five weekdays of each month for these years, and there is information on the timing of commercials for 1,090 contemporary music stations. Listener switching to avoid commercials is a particular problem for contemporary music stations because there may be many quite similar stations in a market which are close substitutes for listeners, they have relatively young audiences which are more likely to switch stations to avoid commercials and they play sequences of distinct songs which do not provide a natural reason for listeners to want to hear what follows immediately after a commercial break.[10]

A section of an airplay log for a Classic Hits (Rock) station is shown in Table 4.1. The log is a list of songs (with artist and release years) with the start time of each song and indicators for whether a commercial break aired between the songs. There is no information on which particular commercials are played. I process each hourly log in the following way to generate the interval data used in estimation:

1. create a minute-by-minute schedule (5:00, 5:01, 5:02 etc.) and mark the start of each song;

2. calculate the median length of each song using those log entries (for all station logs from all hours) where a song is followed by another song with no commercial break;

with 27.4% 10am-3pm and 25% 7pm-midnight (based on data from the Listening Trends section of Arbitron's website, www.arbitron.com)

[10]Median listener ages for Country, Adult Contemporary, Urban, Rock and CHR stations are 44, 41, 29, 26 and 25 compared with 58 and 56 for Classical and News/Talk stations (Katz Media Research website www.krgspec.com). McDowell and Dick (2003) find that younger radio listeners are more likely to switch stations.

Table 4.1: Extract from a 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

3. fill out the schedule with songs assuming that each song is played its median length unless this overlaps another song or would completely eliminate a commercial break where a commercial break is indicated (if step 2 does not provide a length assume that it is 4 minutes, the median length of all of the songs);

4. fill out commercial breaks into the gaps between songs where a commercial break is indicated. Based on personal listening experience and a small sample of more detailed Mediabase logs which give more complete information on what happens during an hour (including, for example, comments by the DJ) it is very rare for there to be more than 6 minutes of commercials in a row. Therefore if there is a gap of more than 6 minutes I assume that the commercial break is played in the middle 6 minutes of the gap.[11]

There is clearly scope for measurement error in this procedure because, even assuming that songs are always played their full length, the logs do not identify periods of DJ chat, news or travel information which may be placed immediately before or after a break. The scope for measurement error is clearly greater when there is a large amount of non-music time in the

[11]For example, if the gap was 8 minutes long then I assume that the commercial break aired between the second and seventh minutes (inclusive). If the gap is, for example, 9 minutes in length I assume that the break aired between the third to the eighth minutes (slightly later than the middle).

hour, so I drop all station-hours with 7 songs or less. This includes hours in which stations have entirely talk programming, such as "The Howard Stern Show", when the airplay log is blank apart from the title of the program. The proportion of station-hours dropped is less than 5% during the midday period (10am-2pm) and the afternoon drive (3-6pm), but greater than 50% during the morning drive when many stations have entirely non-music programming and the other stations have considerable news, weather and travel information and DJ chat.

I now describe the coverage of the sample. I use BIAfn's *Media Access Pro* database to identify each station's home metro-market and its music category. Each stations has one home metro-market based either on its city of license or the market where it has most of its listening. There are 7 music categories in the data: Adult Contemporary, Album Oriented Rock/Classic Rock, Contemporary Hit Radio/Top 40, Country, Oldies, Rock and Urban and the stations are home to 147 different Arbitron-defined local radio metro-markets.[12] Table 4.2 presents some statistics on the number of stations in each metro-market and each metro-market-category and the proportion of contemporary music (the seven categories aggregated together) and category listenership accounted for by the stations in the airplay sample. These proportions are high especially in larger markets and in categories other than Oldies. 14 of the smaller metro-markets contain only one airplay station so I am unable to look at the degree of overlap in these markets.

The airplay sample is unbalanced, as more stations enter the sample over time and there are many individual station-days which are missing. In the year 2000 there are 952 different stations in the data, 48,514 station-days and 929,806 station-hours with some commercials once those station-hours with less than seven songs are dropped. There are 122 metro-markets and 247 metro-market-categories with more than one station. In the year 2001 there are 1,090 different stations in the data, 51,551 station-days and 1,040,779 station-hours with some commercials once those station-hours with less than seven songs are dropped. There are 133 metro-markets and 291 metro-market-categories with more than one station.

Additional data on stations, including listenership and station ownership information, come from BIAfn's *Media Access Pro* database. I measure listenership using Arbitron's average

[12]Stations inform BIAfn of their format and BIA classifies each format into a music category which tries to group together stations playing broadly similar music.

quarter hour (AQH 12+) listenership shares (a station's share of total radio listenership in its market among people aged 12 and above for a broadcast week of Monday-Sunday 6am-12pm). The database also includes an ownership transaction history for each station. In cases where a single radio group owns several different firms which, in turn, own radio stations I define ownership at the group level. One problem is that for all but a station's most recent transaction BIAfn lists the announcement date of the deal rather than the date on which the transaction was completed. However, I use an early 2002 version of the database and there are relatively few stations with more than one transaction between January 2000 and early 2002 so using the announcement data for these transactions should have little effect.

4.4 Empirical Specifications

4.4.1 Concentration of commercials at the metro-market or metro-market category level

I investigate how the observed average overlap of commercials varies with market characteristics using a linear regression specification

$$OVERLAP\_MEASURE_{mdh} = X_{mdh}\beta_1 + D_d\beta_2 + W_d\beta_3 + H_h\beta_4 + \varepsilon_{mdh} \tag{4.9}$$

where m, d and h denote market, day and hour respectively and D_d, W_d and H_h are day of week, week and hour dummies. I consider markets defined to include all music stations which are home to the metro-market and markets which include all stations which are home to the same metro-market and the same music category. The appropriate definition depends on how much switching there is across categories, especially by listeners who want to avoid commercials. As I discuss in Section 4.5 there is evidence that there is a lot of cross-category switching. I will describe the construction of the dependent variable in a moment. X_{mdh} are a set of market characteristics on which the overlap of commercials may depend. They include:

$NUMBER\_STATIONS$: the number of rated stations which are home to the market.[13] This includes stations which are not in my airplay data on a particular day because it is the

[13]Rated stations are commercial stations which have non-zero listening shares recorded by Arbitron.

total number of stations in the market which is relevant.

$HOME\_LISTENING$: the proportion of listenership which is to stations which are home to the market. In some markets (for example, Nassau-Long Island) a large proportion of listening is to stations which are not home to the market but are located in nearby, and typically larger, markets (for example, New York City). If listeners switch to stations outside of a market to avoid commercials, then more out-of-market listening would be expected to have a similar impact to a greater number of home-to-market stations, so $NUMBER\_STATIONS$ and $HOME\_LISTENING$ should have opposite signs.

$HHI\_HOMEMARKET$: the HHI of the rated stations which are home to the market which reflects the ownership structure of the stations. In constructing this measure each station is weighted equally, so an owner's share is its share of stations rather than, for example, these stations' combined shares of listenership or advertising revenues.

$LISTENERSHIP\_ASYMMETRY$: a measure of the asymmetry in the listening shares of the stations, based on their listening shares reported by Arbitron for the ratings quarter in which the day occurs or the next ratings quarter if the market is only rated in two quarters per year. Asymmetries in listenership could plausibly affect the degree of coordination. For example, if small stations or new entrants might choose different times for commercials in order to get listeners to sample their music so that listeners are more likely to return to them in the future or stations with very large market share might act as leaders in coordination. I calculate the measure as $\frac{\sum_{i=1}^{N}\left(\frac{s_i}{\sum_{i=1}^{N} s_i}\right)^2}{\frac{1}{N}}$ where N is the number of rated music stations which are home to the market and s_i is i's share of the listenership to home to market music stations. The numerator is an HHI of station listenership (ignoring station ownership) and the denominator is the value that this HHI would have if stations had equal shares of listenership.

$MEAN\_QUANTITY$: the average number of minutes of commercials played on the stations in the market-day-hour which are in the Mediabase data and have any commercials during the hour. It is plausible that quantities could affect the degree of coordination because, for example, listeners may be more likely to switch if the number of commercials is relatively large. Of course, quantities are potentially endogenous to the degree of coordination in the timing game and in Section 4.5 I describe some results where I instrument for the quantity of commercials.

QUANTITY_ASYMMETRY: a measure of the asymmetry in the quantity of commercials played on each station in the market-day-hour. It is plausible that asymmetries in the quantities could affect the degree of coordination because, for example, if some stations have fewer commercials they might have less incentive to coordinate. This is calculated in the same way as the listenership asymmetry measure but with i's quantity of commercials replacing i's share of listenership.

The dependent variable, *OVERLAP_MEASURE*, measures the extent to which commercials overlap in a market. It is designed to measure how much more (or less) the commercials in a market overlap than they would if station timing decisions were not correlated, conditional on the category and number of minutes of commercials on each station and the hour of the day. To form this benchmark, I estimate what would be the expected overlap if each station in its particular category and with its particular number of minutes of commercials decided on its timing of commercials by drawing randomly from the set of times for all stations in the same category and with the same number of minutes of commercials in the same hour. To do this I perform exactly this randomized procedure 50 times for every station in each market-day-hour. For the actual realized times and each of these repetitions I measure the overlap of commercials within a market in repetition r as $CONC_r = \sum_{m=0}^{59} \left(\frac{\sum_{i=1}^{N} I_{imr}}{\sum_{m=0}^{59} \sum_{i=1}^{N} I_{imr}} \right)^2$ where I_{imr} is an indicator which is 1 if station i has a commercial in minute m in repetition r. I calculate the average of this measure for the 50 repetitions (*MEAN_CONC*). Its variance depends on the number of stations and the number of minutes of commercials each of them has, so I calculate the standard deviation (*SD_CONC*) of the repetitions and create a normalized measure to use as the dependent variable as

$$OVERLAP\_MEASURE_{mdh} = \frac{CONC_{ACTUAL,mdh} - MEAN\_CONC_{mdh}}{SD\_CONC_{mdh}} \qquad (4.10)$$

Note that *OVERLAP_MEASURE* might be greater than zero on average not because stations are trying to choose the same times for commercials as each other but because there are market specific factors which make some times more attractive for commercials for each station in the market, independent of the times being chosen by other stations. For example, if the afternoon commuting period peaks at 4:30 pm in some markets and at 5:00 pm in others this might lead to some markets tending to have earlier commercials during the afternoon drive than other markets. This is one motivation for trying to test whether, and how, the degree of overlap varies with market characteristics as well as just calculating the value of $OVERLAP\_MEASURE$. Of course, there is still an identifying assumption that the degree to which some times of each hour are more attractive is not correlated with market characteristics.[14]

I estimate (4.9) with and without market-hour dummies (fixed effects). With the dummies the coefficients are identified from how the degree of commercial overlap changes when there are changes in, for example, the number of stations in the market or the degree of common ownership. If we assume that any market-specific unobservables which affect timing, such as the timing and length of the afternoon commuting peak, are fixed across the sample period, which is highly plausible, then the fixed-effects specification guards against the possibility that the coefficients simply reflect correlations between these unobservables and the included market characteristics. I also estimate the "between" regression in which I examine how market-hour average of $OVERLAP\_MEASURE$ varies with characteristics across markets rather than within markets.

4.4.2 Overlap of commercials between pairs of stations

I also examine which pairs of stations within markets are more coordinated. I use a linear regression specification

$$PAIR\_OVERLAP\_MEASURE_{ijmdh} = X_{ijmdh}\beta_1 + D_d\beta_2 + W_d\beta_3 + H_h\beta_4 + \varepsilon_{ijmdh} \quad (4.11)$$

for stations i and j which are both home to metro-market m in hour h on day d. I define a pair based on the identity of stations' categories as well as the identity of the stations so that if a pair changes category it becomes a member of a new set of pairs. X_{ijmdh} are variables reflecting the characteristics of the pair at that time. These are:

$SAME\_CATEGORY$: a dummy which takes value 1 if the stations are in the same music

[14]For example, suppose that stations want to play commercials at the peak of drivetime and that the peak last a long time in some cities and a short time in others. We would expect commercials to overlap more in the markets with short drivetime peaks. This could potentially be correlated with the number of stations in the market and the proximity of nearby larger markets, which affects the degree of outside listening.

category.

SAME_OWNER: a dummy which takes value 1 if the stations have the same owner.

SAME_CATEGORY_OWNER: a dummy which takes value 1 if the stations are both in the same category and have the same owner.

MEAN_QUANTITY: the average number of minutes of commercials on each of the stations in the pair-day-hour.

QUANTITY_ASYMMETRY: a measure of the asymmetry in the number of minutes of commercials on each station, calculated as simply the difference in the number of minutes of commercials on the two stations.

MEAN_LISTENERSHIP: a measure of whether the stations have relatively large shares of the their market's listenership, calculated by dividing their average shares by the average share of any home to market station with positive listenership.

LISTENERSHIP_ASYMMETRY: a measure of the asymmetry in listenership shares, calculated by dividing the difference in their shares by the average share of any home to market station with positive listenership.

CLOSE_FREQUENCY: a dummy which measures whether the stations have close FM frequencies. If listeners scan between stations along the frequency dial we would expect stations which are close together to be more coordinated or differentiated. This dummy is 1 if there are no more than two contemporary music stations between them on the FM dial (it is zero if either of the stations is one of the 3 AM stations in the data).[15] I also include a dummy *CATEGORY_CLOSE_FREQUENCY* if the stations are in the same music category ans there is no more than one station in the same category between them on the FM dial.

The construction of the *PAIR_OVERLAP_MEASURE* variable follows the same logic as the construction of the *OVERLAP_MEASURE* used in the market level regressions. Using the actual data I form all possible pairs of stations from the same metro-market. I then use the same randomized drawing procedure as before to create 50 repetitions of the pair by drawing same stations from the same categories with the same number of commercials in the same hour as the original stations. For both the original data and each of the repetitions I

[15]For example, suppose that contemporary music stations A, B, C, D and E are at 94.1, 95.2, 96.3, 97.4 and 98.5 respectively. Then *CLOSE_FREQUENCY* would be one for all pairs apart from A and E.

count the number of minutes in which both stations have commercials ($MINS\_OVERLAP$). I then calculate the mean and standard deviation of $MINS\_OVERLAP$ for the 50 repetitions, $MEAN\_OVERLAP$ and $SD\_OVERLAP$, and form $PAIR\_OVERLAP\_MEASURE$ as

$$PAIR\_OVERLAP\_MEASURE_{ijmdh} = \frac{MINS\_OVERLAP_{ijmdh} - MEAN\_OVERLAP_{ijmdh}}{SD\_OVERLAP_{ijmdh}} \tag{4.12}$$

I estimate (4.11) in different specifications to examine between pair variation and which pairs are more coordinated within each market-day-hour.

4.4.3 Summary statistics

Tables 4.3(a)-(c) present summary statistics for the variables used in the regression analysis, including the within and between market/pair variance of each variable so that the sources of identification in the data can be better understood.

The average $OVERLAP\_MEASURE$ is positive, except for markets at the metro-market-category level at night, indicating that, on average, commercials within a market overlap more than would be expected based on the nationwide timing patterns for stations in the same categories with the same number of minutes of commercials. To understand the magnitude of the $OVERLAP\_MEASURE$ variable, consider a simple example. Suppose that 2 Rock stations play 12 minutes of commercials between 4pm and 5pm. If their times are chosen by drawing from a uniform distribution across the whole hour, their commercials would be expected to overlap for 144 seconds. If instead commercial times are drawn from the times actually chosen by Rock stations with 12 minutes of commercials between 4pm and 5pm from any market then average amount of overlap is 186.2 seconds.[16] If commercials from stations within a market overlapped by exactly this amount the value of $OVERLAP\_MEASURE$ would be zero. Instead, a value of $OVERLAP\_MEASURE$ of 0.063 (the average value of the measure at the metro-market level during drivetime) would involve commercials overlapping for 196.6 seconds, a 6% increase from 186.2 seconds and 36% increase from 144 seconds. While there is some variation in $OVERLAP\_MEASURE$ between market hours there is more variation within market hours, reflecting the fact that stations do not play their commercials at exactly the

[16]This number was calculated by repeating this drawing process 10,000 times with replacement.

same time from day-to-day, so that the degree of overlap within a market can vary considerably for the same hour on different days. This is true even for days during the same week.

Stations have more commercials on average during drivetime (especially the morning drive) than during other parts of the day and there is variation within quantities both within and between markets. Some of the within-variation is seasonal: for example, there are on average an additional $1\frac{1}{2}$ minutes of commercials per hour in early December than in early January. There is slightly greater variation in the quantity of commercials on each station during the night, when some stations only have a small number of commercials, than during the rest of the day.

Variation in the number of home to market contemporary music stations and in the proportion of rated listening to home to market stations comes primarily from differences between markets, especially when markets are defined at the metro-market level, because these variables are largely determined by a combination of population size, ethnic profile, which influences the number of contemporary music stations relative to Spanish stations, and the proximity of nearby markets. The metro-markets with the most contemporary music stations are Chicago, Pittsburgh and Salt Lake City-Ogden and in all three of these markets all rated listening is to stations which are home to the market. Smaller markets close to larger markets have few home to market stations and most of the listening is to stations outside of the market. For example, there are only 3 rated contemporary music stations home to Akron and 80% of listening in Akron is to outside stations, mainly located in Cleveland. There is relatively more variation in these variables within markets defined at the metro-market category level because entry, exit or category switching by individual stations or changes in individual stations shares of listenership have a proportionally larger effect. Also most of the metro-market category markets are located in relatively large metro-markets, for example 50% are from the largest 41 of the 133 metro-markets in the data. Metro-markets with large asymmetries in station listenership shares tend to be medium-sized and smaller markets, where a small number of stations have large shares, rather than the largest markets. For example, in Knoxville, TN in Fall 2001 there were 15 contemporary music stations with non-zero listening shares but the largest station accounted for 34% of music listenership and the largest three stations accounted for 63% of music listenership. The average HHI for contemporary music stations is 0.237 reflecting the fact that by the year 2000 there was significant station cross-ownership. On average, the HHI is higher in smaller metro-markets with fewer home to market stations. There is also some variation in ownership concentration over the sample period reflecting merger activity and station sales.

Table 4.3(c) gives the summary statistics for variables defined for station-pairs in the same metro-market. The number of pairs is huge, but as I describe in the notes to Table 4.6 I only use a sample of pairs which are neither commonly owned nor in the same category in the regressions. The $PAIR\_OVERLAP\_MEASURE$ is greater than zero, on average, for all 3 dayparts and consistent with the market-level overlap measures it varies more within pairs than between pairs. 621 different pairs of stations are in the same category and 1,036 pairs are ever commonly owned, including 143 pairs which change whether they are commonly owned while they are in the data. 136 pairs in the same category are commonly owned at some point. It is these relatively small number of pairs which identify the $SAME\_CATEGORY$, $SAME\_OWNER$ and $SAME\_CATEGORYOWNER$ coefficients, although of course there are multiple observations on each pair from different hours and days. On average, the listenership of the stations in the Mediabase sample is greater than the average contemporary music station in their market so $MEAN\_LISTENERSHIP$ is on average greater than 1. Variation in the listenership variables within pairs over time reflects changes in stations' shares of listenership.

4.5 Empirical Results

4.5.1 Concentration of commercials at the metro-market level

The regression results when markets are defined at the metro-market level are presented in Table 4.4(a). The first three columns given the results for the three different dayparts when the observations from different market-hours are pooled in the same regression. Standard errors are robust to heteroskedasticity and clustered at the level of the market so that observations from the same market on different hours or on different days are not assumed to be independent. For the drivetime hours the $NUMBER\_STATIONS$ and $HOME\_LISTENING$ coefficients are significant at the 5% level and an increase in the number of home to market stations or in the amount of listening to stations outside of the market is predicted to decrease the degree of coordination. These coefficients, together with the positive sign of the $HHI\_HOMEMARKET$ coefficient which is not significant, are consistent with a model where stations want to choose the same times for commercials but as the number of stations increases the degree of coordination which can be sustained in equilibrium decreases. To illustrate the magnitude of the estimated effects I will throughout give them in terms of the implied change in the number of seconds commercials on two Rock stations with 12 minutes of commercials between 4 and 5pm would be expected to overlap. Recall from Section 4.4.3 that, on average, their commercials overlap for 196.4 seconds based on the average value of $OVERLAP\_MEASURE$ during drivetime. The coefficient point estimates imply that a one standard deviation increase in $HOME\_LISTENING$ or $HHI\_HOMEMARKET$ or a one standard deviation decrease in $NUMBER\_STATIONS$ would lead to an increase in the overlap of 15.5, 6.1 or 13.4 seconds respectively. The coefficients on these variables have the same sign and are of roughly similar magnitude during the daytime and night hours although the coefficients are less significant. Of the remaining variables of interest, $LISTENERSHIP\_ASYMMETRY$ is positive and significant at the 5% level in each of the dayparts and indicates that stations tend to play commercials at the same time more in markets where there are greater asymmetries in listenership. This is not what one would expect if stations with small listenerships are trying to increase their shares by getting listeners from larger stations to sample their music, but it is consistent with a situation where a number of smaller stations want to coordinate with just one or two stations which are clearly market leaders. The drivetime coefficient implies that one standard deviation increase in this variable is associated with a 9.2 second increase in the overlap. $MEAN\_QUANTITY$ is negative in each hour, but only significant outside drivetime. Given that there should be less incentive to coordinate or differentiate outside drivetime when fewer listeners switch stations it is not clear what explains this result. The daytime coefficient implies that a one standard deviation in $MEAN\_QUANTITY$ is associated with an increase in the amount of overlap by 8.6 seconds.

Columns (4)-(6) give the results of the between regressions for each daypart where the average amount of overlap in each market is regressed on average market characteristics. Recall from Table 4.3(a) that the majority of variation in the number of stations in the market or in the amount of home listening comes from between markets because these variables are largely determined by market-size and geography. For my sample period most of the variation in $HHI\_HOMEMARKET$ also comes from between markets. The $NUMBER\_STATIONS$, $HOME\_LISTENING$, and $HHI\_HOMEMARKET$ coefficients are all significant, at least at the 10% level, during drivetime but only one of the six coefficients is significant for the other two dayparts. The significance of these variables is impressive given that there are only 133 different metro-markets in the data to provide variation in these variables. The drivetime $HHI\_HOMEMARKET$ coefficient is larger than before, implying that a one standard deviation increase in this variable is associated with an increase in the expected overlap of 11.7 seconds. $LISTENERSHIP\_ASYMMETRY$ is again significant in all of the dayparts, with coefficients of very similar size. While the drivetime coefficients are not generally significantly greater than the coefficients outside drivetime, it is noticeable, and consistent with the theory that some of the observed overlap of commercials within markets results from stations trying to choose the same times for commercials, that the results are generally more statistically significant during drivetime.

Columns (7)-(9) give the results from the within regressions for each daypart. The coefficients are identified from how changes in the variables within a market-hour during the sample period are associated with changes in the extent to which commercials overlap. Consistent with the fact that the number of stations or the amount of outside listening vary little within-market all of the $NUMBER\_STATIONS$ and $HOME\_LISTENING$ variables are insignificant. $LISTENERSHIP\_ASYMMETRY$ is now insignificant and it also varies largely across markets (smaller markets tend to have more asymmetric listenership). For this reason it is a little surprising that $HHI\_HOMEMARKET$ is significant at the 10% level during drivetime. Consistent with the pooled and within coefficients, an increase in ownership concentration is associated with an increase in the extent to which commercials overlap, consistent with the idea that, on average, the incentive of stations is to coordinate. The only other coefficient which is significant at all is $QUANTITY\_ASYMMETRY$, at the 10% level during daytime. The coefficient is negative even though in all of the other columns the coefficient is positive, but insignificant, suggesting that little weight should be placed on this result.

Table 4.4(b) gives the results of the same set of regressions replacing $NUMBER\_STATIONS$, $HOME\_LISTENING$ and $MEAN\_QUANTITY$ with their natural logarithms because the effects of these variables might be non-linear. The pattern of significance, signs and magnitudes of the coefficients are very similar to Table 4.4(a), although some of the $NUMBER\_STATIONS$ and $HOME\_LISTENING$ slightly increase in statistical significance outside drivetime. The results which are most consistent with a theory that stations, on average, want to choose the same times for commercials are, again, the between market results.

The quantity of commercials is potentially endogenous to the outcome of the timing game.[17] For example, if stations coordinate closely on timing then, because listeners are less able to avoid commercials, stations may be able to increase the quantity of commercials they play. On the other hand, if many listeners avoid commercials advertisers may want to play more commercials so that their commercials are heard a sufficient number of times to be effective. There are two concerns: first that endogeneity leads to misleading estimates of the coefficients on the quantity variables and second that it leads to misleading estimates of the coefficients on the other variables, such as $HHI\_HOMEMARKET$. An ideal instrument for quantity is a demand shifter from the advertising market. An analysis of the quantity of commercials reveals that there are more commercials in the months just before Christmas and less immediately after the New Year, more commercials towards the end of the week than on Mondays and some differences in the quantities of commercials across hours (for example, fewer very early in the morning). In Tables 4.4(a) and 4.4(b) hour, week and day of week dummies are included as controls for the degree of coordination on timing but they are not particularly significant. For example, in the pooled cross-section regression in column (1) of Table 4.4.1 none of the 34 dummies is individually significant at the 1% level and the statistic for the test that they are all equal to zero is 2.48. In contrast, in a regression of $MEAN\_QUANTITY$ on these dummies, the majority of the coefficients are individually highly significant and the F-statistic for the test that they are jointly zero is 157.85. This suggests that it may be reasonable to exclude these dummies from the overlap equation and instead use them as instruments for quantity. In Table 4.4(c) I reproduce the results of Table 4.4(d) without including the quantity variables or the time dummies. Almost all of the coefficients are very close to

[17] I note that one could also argue that the $LISTENING\_ASYMMETRY$ is also endogenous if the timing of commercials affects the flow of listeners between channels. However, it seems unlikely that timing would have a large effect on average station listening (to both commercials and music) even if it has a significant effect on the audience of commercials.

their values in Table 4.4(a) with a similar pattern of significance for $NUMBER\_STATIONS$, $HOME\_LISTENING$ and $LISTENERSHIP\_ASYMMETRY$. The exception are the coefficients on $HHI\_HOMEMARKET$ in the between and within specifications for the drivetime and daytime hours which fall in size and are only significant at the 10% level. Table 4.4(d) gives the IV results when I use the time dummies to instrument for $MEAN\_QUANTITY$. As I do not have an obvious instrument for $QUANTITY\_ASYMMETRY$ and it was insignificant in all but one specification in Table 4.4(a), I do not include it in the regressions. The point estimates of the coefficients are very similar to those in Table 4.4(c), but the $HHI\_HOMEMARKET$ coefficients fall slightly so that they are just insignificant at the 10% level. I conclude that dealing with the endogeneity of quantities has very little effect on the non-quantity coefficients, with the partial exception of $HHI\_HOMEMARKET$. The quantity coefficient itself shows no clear pattern, with varying sign, apart from being highly significant in column (7), where the coefficient implies that a one standard deviation increase in the quantity of commercials would increase the overlap of commercials on the two Rock stations by 12 seconds.

4.5.2 Concentration of commercials at the metro-market-category level

Table 4.5(a) presents the results when markets are defined at the metro-market-category level rather than at the metro-market level. If listeners primarily switch between stations in the same music category we would expect to see stronger evidence of coordination at the metro-market category level than at the metro-market level. On the other hand, if most listeners switch between categories, partly reflecting the difficulties involved in defining categories well, then the degree of coordination might be determined by characteristics measured at the metro-market level rather than the metro-market-category level. The table is organized in the same way as Table 4.4(b) and I present the log results although the results without logs are very similar. Fewer of the coefficients are significant than before, even in the between specification, although their signs are largely the same as for the metro-market level analysis with the degree of coordination appearing to decline as the number of stations or the proportion of out of market listenership increases, or the asymmetry between stations' shares of listenership decreases. The size of the implied effects is also slightly smaller than before. For example, the $LN(NUMBER\_STATIONS)$ coefficient in column (1) implies that a 1 standard deviation increase in the number of stations would reduce the expected overlap by 6.5 seconds and a 1 standard deviation increase in the proportion of listening which is to stations which are home to the market increases the expected overlap by 5.1 seconds. The point estimate of $HHI\_HOMEMARKET$ implies that a 1 standard deviation increase in the ownership concentration increases overlap by less than one second.

There are three possible explanations for why the results are weaker at the metro-market-category level. The first is that many listeners do switch across categories to avoid commercials so that measuring market characteristics at the metro-market-category level may mismeasure the variables that matter from the perspective of stations. I was able to collect, for the Boston metro-market, Arbitron's estimates of cross-station listenership for Fall 2002 (Arbitron (2003)) which give the proportion of listeners to station i who also listen to station j. In Boston there are 6 Rock stations and 9 non-Rock contemporary music stations in the airplay data. On average, 18.4% of the listeners to one of the Rock stations listens to each of the other 5 Rock stations while on average 17.1% of the listeners to one of the Rock stations listens to each of the 9 non-Rock stations indicating that even in a category where there are several stations playing quite similar music people who listen to those stations still also listen to stations in other categories. The second explanation is that when I define markets at the metro-market level much of the variation in the number of stations or the proportion of out of market listening is caused by geography which provides a cleaner source of variation than variation in the number of stations in a music category which is more likely to be influenced by difficulties in classifying individual stations. For example, a Classic Rock station in the Album Oriented Rock/Classic Rock category may play quite similar music to a Classic Hits station in the Rock category. In addition, the metro-market-categories where I can measure overlap, i.e., where there is more than one station in the airplay sample, come primarily from the larger metro-markets where the metro-market results suggests that there may be less coordination (the largest markets tend to have many stations, lower HHIs and more symmetric shares of listenership).[18] Table 4.5(b) therefore gives the results when I re-run the specifications in Table 4.5(a) but drop metro-

[18]I calculated the predicted level of $OVERLAP\_MEASURE$ for each metro-market-hour from the between regression for drivetime in column (4) of Table 4(a). The correlation coefficient between the prediction and the rank of the metro-market (with the largest, New York City at 1) was 0.3922 indicating that smaller markets tend to be more coordinated.

market categories from the largest 10 metro-markets. The majority of the coefficients either increase in absolute magnitude or remain the same size as before. In particular, an increase in the number of stations in the category is more clearly associated with less coordination in the pooled cross-section regressions and the effects are also larger, but largely not significant in the between regression. The column (1) coefficient implies that a 1 standard deviation increase in the number of stations (from 3.1 to 4.3) decreases overlap by 8 seconds. In the within-market results, increases in ownership concentration are associated with increased overlap. The daytime effect is estimated to be large: a 1 standard deviation increase in the HHI is associated with a 20 second increase in the overlap. The ownership coefficients are also estimated to be larger than before in the between regressions. The listenership asymmetry coefficients also increase in size in every specification and are significant at the 5% level during drivetime and daytime in 5 out of the 6 cases. Therefore it seems that at least part of the weaker results at the metro-market level may come from the fact that the some of the relationships which support the theory that stations want to coordinate do not apply in the very largest markets.

The third possibility is that some stations playing very similar music want to choose the same times for commercials and that other stations want to choose different times for commercials, so that the mean effects are insignificant. This is possible if there is heterogeneity in how different kinds of listeners behave or in, for example, their outside options. In this case, characteristics such as greater common ownership might be associated with commercials which overlap a lot or commercials which overlap very little. I estimate quantile regressions to examine whether characteristics matter differently in the tails of the distribution and whether they effect the variance of observed outcomes. In order to keep the computation manageable I estimate conditional quantiles on the between specification, i.e.,

$$Q_\tau(\overline{y}_{mh}|\overline{x}_{mh}) = \overline{x}_{mh}\beta_\tau \tag{4.13}$$

where $\overline{y}$ is the average $OVERLAP\_MEASURE$ in metro-market–category hour mh and $\overline{x}_{mh}$ are the average mh characteristics and τ defines the quantile of interest. I estimate 10^{th} and 90^{th} quantile functions and the range between these quantiles. The results are presented in Table 4.5(c). Standard errors are clustered at the level of the metro-market-category using a bootstrap with 100 repetitions.

Very few of the coefficients are individually significant. In particular the 10^{th} quantile results do not provide any real evidence that some stations are trying to differentiate their timing. The most significant results indicate that greater asymmetry in quantities is associated with less coordination at the highest quantiles, indicating that the outcomes with the most overlap are associated with stations having reasonably symmetric quantities. This result holds in all dayparts. However, it is not easy to explain especially as the individual stations' choice of quantities could well be somewhat endogenous to the outcome of the timing game.

4.5.3 Coordination between pairs of stations in the same metro-market

Table 4.6 presents the results when I regress the degree of overlap of commercials on a pair of stations on the characteristics of the pair. The regressions use a sample of pairs which are not commonly owned and not in the same category to keep the analysis manageable. Columns (1)-(3) give the results when all the observations are pooled. Columns (4)-(6) give the results from the between pair regressions. Columns (7)-(9) examines which are most coordinated pairs within a metro-market-day-hour, using metro-market-day-hour dummies to control for the average degree of coordination in the market on a particular day-hour.

The results are somewhat disappointing. In particular, commonly owned stations in the same music category are neither significantly more coordinated or less coordinated than the average pair in the same category in eight of the nine specifications, the exception being for the between specification during the night, when commonly owned stations are less coordinated at the 10% significance level (adding the $SAME\_CATEGORYOWNER$ and the $SAME\_OWNER$ coefficients). The magnitude of the combined coefficient indicates that commercials on the two Rock stations overlap by 8.5 seconds less when they are commonly owned than when they are separately owned and in the same category. One possible explanation is that because commonly owned stations within a category tend to differentiate themselves in terms of the music that they play, as described in Sweeting (2004b), fewer listeners switch between these stations and it is less important for them to coordinate on the timing of commercial breaks. The estimates in the other columns also imply that the commonly owned category-pairs are less coordinated, even though the effects are not significant. This is obviously surprising given that common ownership appeared to be associated with greater overlap of commercials at the metro-market and metro-market category level. While none of the $SAME\_OWNER$ coefficients are significant and all of them are small, commonly owned stations in different categories are slightly more coordinated than separately owned pairs. In four columns, a greater average quantity of commercials is associated with less coordination although when I examine which pairs are more coordinated within a market these effects almost completely disappear.

4.6 Conclusion

While music stations play commercials at the same time it is unclear how much of this pattern reflects the equilibrium of a timing game with significant interactions between the stations as players and how much it simply reflects the fact that some times are more attractive for commercials for any station independent of which times other stations choose. The approach taken in this paper has been to identify several factors which we would expect to affect the degree of coordination in equilibrium if there are strategic interactions and to test whether they do, in practice, appear to affect the observed degree of coordination. In addition, the way in which characteristics such as common ownership affect the observed degree of coordination can potentially tell us whether stations want, on average, to coordinate or to differentiate on the timing of their commercial breaks.

When I examine the degree of coordination amongst all of the stations which are home to a metro-market I find that commercials tend to overlap more in markets with fewer home to market stations, in markets where there is less listening to out of market stations and in markets where there is more concentrated ownership. In addition, these effects are more statistically significant during drivetime, and larger during drivetime and daytime than at night when fewer listeners switch stations. These findings are consistent with a model where, on average, stations want to choose the same times for commercials as other stations in their market and suggests that the high degree to which commercials overlap is partly due to strategic interaction. The evidence at the metro-market-category level is weaker, even though it does not contradict the metro-market results especially outside of the largest 10 metro-markets. The metro-market-category results may be weaker because many listeners switch between music stations in different categories so that the degree of coordination depends on the characteristics of the market as a whole. In addition the metro-market results indicate that there is most coordination in relatively small, isolated markets, where HHIs also tend to be higher than in the largest markets, that there is the most coordination and these markets are underrepresented when I look at the degree of coordination at the metro-market-category level. On the other hand, when I examine individual pairs of stations, commonly owned stations in the same category appear to be less rather than more coordinated than an average pair of stations in the same category, and while this is inconsistent with a simple story where all stations prefer to choose the same times for commercials, these differences are generally not significant.

An obvious question is whether coordination on timing has implications for welfare. If listeners who dislike commercials are unable to avoid them this may reduce the welfare of listeners but increase the welfare of advertisers who are able to charge more for their commercials. In addition, even listeners who dislike commercials may benefit indirectly if the resulting increased value of commercial time leads to a greater number of stations being supported.

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Table 4.2: Coverage of the Airplay Sample
Based on Fall 2001 Categories and Station Ratings

Category	Number of Metro-Market Categories (MMCs) with Home to MMC Stations in the Airplay Sample	Number of Home to MMC Rated Stations	Number of Home to MMC Stations in Airplay Sample	Average % of Listening to Home to MMC Stations Accounted for by the Airplay Sample
Arbitron Metro-Markets Ranked 1-70 (1 is New York City and 70 is Ft. Myers, FL)				
All contemporary music	69	1003	716	85.7
Adult Contemporary (AC)	66	221	161	89.0
Album Oriented Rock/Classic Rock (AOR)	65	111	98	95.8
Contemporary Hit Radio/Top 40 (CHR)	64	131	111	94.9
Country	64	141	94	92.1
Oldies	44	64	44	92.1
Rock	61	147	122	94.0
Urban	44	133	86	85.1
Arbitron Metro-Markets Ranked 70 and above (71 is Knoxville, TN)				
All contemporary music	78	759	374	68.8
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	81	60	86.7
Urban	27	58	39	86.2

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

Table 4.3(a): Summary Statistics when Market Defined at the Metro-Market Level

Variable	Daypart	Number of Observations	Mean	Standard Deviation			Minimum	Maximum
				Total	Between	Within		
OVERLAP_MEASURE	Drivetime (6-9am & 3-7pm)	104,349	0.063	1.067	0.449	0.971	-3.204	9.902
	Daytime (10am-2pm)	70,386	0.097	1.082	0.474	0.977	-3.251	7.431
	Night (7pm-5am)	121,898	0.077	1.099	0.402	1.025	-3.008	14.000
MEAN_QUANTITY	Drivetime (6-9am & 3-7pm)	104,349	13.091	3.564	2.901	2.235	1.500	29.500
	Daytime (10am-2pm)	70,386	10.420	1.895	1.171	1.575	1.000	21.000
	Night (7pm-5am)	121,898	8.092	2.784	2.383	1.621	1.000	19.000
QUANTITY_ASYMMETRY	Drivetime (6-9am & 3-7pm)	104,349	1.085	0.089	0.044	0.080	1.000	2.210
	Daytime (10am-2pm)	70,386	1.083	0.079	0.038	0.071	1.000	2.190
	Night (7pm-5am)	121,898	1.192	0.168	0.099	0.138	1.000	2.955
NUMBER_STATIONS	All	323,266	13.376	4.126	4.332	0.774	3.000	24.000
HOME_LISTENING	All	323,266	0.876	0.201	0.227	0.013	0.154	1.000
HHI_HOMEMARKET	All	323,266	0.242	0.080	0.087	0.023	0.105	0.625
LISTENERSHIP ASYMMETRY	All	323,266	1.374	0.080	0.209	0.085	1.000	2.740

Table 4.3(b): Summary Statistics when Market Defined at the Metro-Market-Category Level

				Standard Deviation				
Variable	Daypart	Number of Observations	Mean	Total	Between	Within	Minimum	Maximum
OVERLAP_MEASURE	Drivetime (6-9am & 3-7pm)	125,851	0.016	1.055	0.497	0.951	-2.974	6.930
	Daytime (10am-2pm)	112,886	0.022	1.060	0.451	0.96057	-2.372	8.087
	Night (7pm-5am)	177,237	-0.023	1.042	0.395	0.976	-3.985	14.001
MEAN_QUANTITY	Drivetime (6-9am & 3-7pm)	125,851	12.190	3.437	3.065	2.244	1.000	31.000
	Daytime (10am-2pm)	112,886	10.605	2.341	1.567	1.891	1.000	22.000
	Night (7pm-5am)	177,237	8.675	3.280	2.701	2.072	1.000	21.000
QUANTITY_ASYMMETRY	Drivetime (6-9am & 3-7pm)	125,851	1.058	0.100	0.068	0.086	1.000	2.238
	Daytime (10am-2pm)	112,886	1.055	0.091	0.054	0.082	1.000	1.751
	Night (7pm-5am)	177,237	1.112	0.141	0.073	0.125	1.000	2.271
NUMBER_STATIONS	All	450,134	3.140	1.202	1.034	0.451	2.000	9.000
HOME_LISTENING	All	450,134	0.969	0.078	0.082	0.016	0.351	1.000
HHI_HOMEMARKET	All	450,134	0.504	0.212	0.188	0.079	0.184	1.000
LISTENERSHIP ASYMMETRY	All	450,134	1.203	0.239	0.215	0.118	1.000	3.047

Table 4.3(c): Summary Statistics for the Degree of Coordination Between Pairs of Stations in the Same Metro-Market

		Number of Observations	Mean	Standard Deviation Total	Between	Within	Minimum	Maximum
PAIR_OVERLAP_MEASURE	Drivetime (6-9am & 3-7pm)	1,728,374	0.0124	1.039	0.535	0.939	-4.091	14.001
	Daytime (10am-2pm)	1,654,277	0.0102	1.041	0.455	0.949	-3.239	14.001
	Night (7pm-5am)	2,956,045	0.0163	1.055	0.409	0.992	-5.153	14.953
SAME_CATEGORY	All	6,341,839	0.118	0.323	0.325	0	0	1
SAME_OWNER	All	6,341,839	0.199	0.399	0.386	0.073	0	1
SAME_CATEGORYOWNER	All	6,341,839	0.028	0.166	0.153	0.028	0	1
QUANTITY_ASYMMETRY	All	6,341,839	3.811	3.372	2.234	2.809	0	30
MEAN_QUANTITY	All	6,341,839	10.168	3.480	3.272	2.113	1.000	31.000
MEAN_LISTENERSHIP	All	6,341,839	1.565	0.484	0.462	0.150	0.149	5.124
LISTENERSHIP_ASYMMETRY	All	6,341,839	0.672	0.565	0.530	0.248	0.000	6.090
CLOSE_FREQUENCY	All	6,341,839	0.316	0.465	0.466	0	0	1
CATEGORY_CLOSEFREQUENCY	All	6,341,839	0.888	0.301	0.301	0.039	0	1

Table 4.4(a): Metro-Market Level Regressions with OVERLAP_MEASURE as Dependent Variable

	Pooled Cross-Section			Between Market-Hours			Within Market-Hours		
	(1) Drivetime	(2) Daytime	(3) Night	(4) Drivetime	(5) Daytime	(6) Night	(7) Drivetime	(8) Daytime	(9) Night
NUMBER_STATIONS	-0.0202** (0.0098)	-0.0165 (0.0133)	-0.0196 (0.0123)	-0.0182* (0.0105)	-0.0088 (0.0158)	-0.0199 (0.0127)	-0.0181 (0.0166)	-0.0167 (0.0245)	-0.005 (0.0184)
HOME_LISTENING	0.4898*** (0.1793)	0.4535* (0.2348)	0.0964 (0.2105)	0.5009*** (0.1785)	0.2511 (0.2607)	0.1011 (0.2085)	0.2401 (0.6988)	-0.5565 (0.8485)	0.0845 (0.5833)
HHI_HOMEMARKET	0.4738 (0.3693)	0.6962 (0.5061)	-0.3433 (0.3166)	0.9103** (0.3522)	1.2045* (0.6479)	-0.3429 (0.3444)	0.7599* (0.3988)	0.9863 (0.7077)	0.1582 (0.5526)
LISTENERSHIP_ASYMMETRY	0.2441** (0.1010)	0.3833** (0.1521)	0.1982** (0.1005)	0.2523** (0.1167)	0.3505** (0.1721)	0.1885* (0.1145)	0.1936 (0.1675)	0.2358 (0.2106)	0.0799 (0.1513)
MEAN_QUANTITY	-0.0037 (0.0057)	-0.0268* (0.0143)	-0.0164** (0.0081)	-0.0126 (0.0182)	-0.0381 (0.0409)	-0.0307* (0.0163)	0.002 (0.0029)	0.0013 (0.0070)	0.0005 (0.0049)
QUANTITY_ASYMMETRY	0.0479 (0.1035)	0.0255 (0.2026)	0.0324 (0.0603)	0.4126 (0.5033)	1.1106 (1.2197)	0.0306 (0.2488)	0.0202 (0.0610)	-0.1766* (0.0942)	0.0154 (0.0409)
Dummies	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day Metro-Market	Hour Week Day Metro-Market	Hour Week Day Metro-Market
R^2 (including dummies)	0.0083	0.0129	0.0081	0.1255	0.2279	0.1300	0.0018	0.0037	0.0042
Number of observations	104,349	70,386	121,898	104,349	70,386	121,898	104,349	70,386	121,898

Notes: 1. Standard errors in parentheses robust to heteroskedasiticty and clustered at the metro-market level
2. Drivetime hours are 6:00am-9:59am & 3:00pm-6:59pm, daytime hours are 10:00am-2:59pm and night hours are 7:00pm-5:59am.
3. R^2 for between (within) regressions reflects the degree of between (within) market variation explained by the regressors.

Table 4.4(b): Metro-Market Level Regressions with OVERLAP_MEASURE as Dependent Variable

	Pooled Cross-Section			Between Market-Hours			Within Market-Hours		
	(1) Drivetime	(2) Daytime	(3) Night	(4) Drivetime	(5) Daytime	(6) Night	(7) Drivetime	(8) Daytime	(9) Night
LN(NUMBER_STATIONS)	-0.3148*** (0.1062)	-0.2511* (0.1473)	-0.2788** (0.1290)	-0.3233*** (0.1086)	-0.2196 (0.1661)	-0.2738** (0.1284)	-0.2615 (0.2353)	-0.1809 (0.3456)	0.0808 (0.2632)
LN(HOME_LISTENING)	0.4332*** (0.1092)	0.3793** (0.1507)	0.1630 (0.1379)	0.4629*** (0.1118)	0.2738 (0.1722)	0.1609 (0.1326)	0.1528 (0.2593)	-0.5055* (0.2969)	-0.1409 (0.2463)
HHI_HOMEMARKET	0.3722 (0.3872)	0.621 (0.5369)	-0.4136 (0.3325)	0.7768** (0.3683)	1.0174 (0.6663)	-0.405 (0.3452)	0.7001* (0.4220)	0.9944 (0.7530)	0.279 (0.5688)
LISTENERSHIP_ASYMMETRY	0.2422** (0.0983)	0.3792*** (0.1492)	0.2041** (0.0984)	0.2580** (0.1120)	0.3584** (0.1722)	0.1938* (0.1135)	0.2057 (0.1763)	0.2344 (0.2175)	0.0277 (0.1584)
LN(MEAN_QUANTITY)	-0.0713 (0.0742)	-0.2636** (0.1233)	-0.0941* (0.0530)	-0.2287 (0.2289)	-0.4453 (0.4044)	-0.1491 (0.1052)	0.0362 (0.0346)	0.0136 (0.0603)	0.0047 (0.0314)
QUANTITY_ASYMMETRY	0.0289 (0.1039)	0.0305 (0.1989)	0.0604 (0.0611)	0.347 (0.4952)	0.9816 (1.2259)	0.1038 (0.2596)	0.0287 (0.0603)	-0.1741* (0.0933)	0.015 (0.0404)
Dummies	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day Metro- Market	Hour Week Day Metro- Market	Hour Week Day Metro- Market
R^2 (including dummies)	0.0101	0.0141	0.0082	0.1393	0.2333	0.1183	0.0018	0.0034	0.0041
Number of observations	104,349	70,386	121,898	104,349	70,386	121,898	104,349	70,386	121,898

Notes: 1. Standard errors in parentheses robust to heteroskedasiticty and clustered at the metro-market level
2. Drivetime hours are 6:00am-9:59am & 3:00pm-6:59pm, daytime hours are 10:00am-2:59pm and night hours are 7:00pm-5:59am.
3. R^2 for between (within) regressions reflects the degree of between (within) market variation explained by the regressors.

Table 4.4(c): Metro-Market Level Regressions with OVERLAP_MEASURE as Dependent Variable without Quantity Variables

	Pooled Cross-Section			Between Market-Hours			Within Market-Hours		
	(1) Drivetime	(2) Daytime	(3) Night	(4) Drivetime	(5) Daytime	(6) Night	(7) Drivetime	(8) Daytime	(9) Night
NUMBER_STATIONS	-0.0207** (0.0098)*	-0.017 (0.0133)	-0.0207 (0.0122)	-0.0185* (0.0104)	-0.0127 (0.0142)	-0.0171 (0.0128)	-0.0243 (0.0175)	-0.0326 (0.0257)	-0.0281 (0.0191)
HOME_LISTENING	0.4846*** (0.1798)	0.4893** (0.2376)	0.1155 (0.2084)	0.4646** (0.2045)	0.4644* (0.2577)	0.0655 (0.2155)	0.3275 (0.6939)	-0.5091 (0.8333)	0.1277 (0.5913)
HHI_HOMEMARKET	0.4824 (0.3696)	0.7286 (0.5127)	-0.3473 (0.3199)	0.6909* (0.4168)	0.9652* (0.5839)	-0.2283 (0.3529)	0.6842* (0.4013)	0.7925 (0.7100)	-0.1171 (0.5952)
LISTENERSHIP_ASYMMETRY	0.2501** (0.1011)	0.4072** (0.1576)	0.2202** (0.1019)	0.2602** (0.1146)	0.3881** (0.1806)	0.2076* (0.1122)	0.2338 (0.1683)	0.3468* (0.2083)	0.2466* (0.1360)
Dummies	None	None	None	None	None	None	None	None	None
R^2 (including dummies)									
Number of observations	104,349	70,386	121,898	104,349	70,386	121,898	104,349	70,386	121,898

Notes: 1. Standard errors in parentheses robust to heteroskedasiticty and clustered at the metro-market level
2. 2. Drivetime hours are 6:00am-9:59am & 3:00pm-6:59pm, daytime hours are 10:00am-2:59pm and night hours are 7:00pm-5:59am.
3. R^2 for between (within) regressions reflects the degree of between (within) market variation explained by the regressors.

Table 4.4(d): Metro-Market Level Regressions with OVERLAP_MEASURE as Dependent Variable With Hour, Week and Day of Week Dummies as Instruments for Quantity

	Pooled Cross-Section			Between Market-Hours			Within Market-Hours		
	(1) Drivetime	(2) Daytime	(3) Night	(4) Drivetime	(5) Daytime	(6) Night	(7) Drivetime	(8) Daytime	(9) Night
NUMBER_STATIONS	-0.0208**	-0.0169	-0.0207*	-0.0188*	-0.0126	-0.017	-0.0225	-0.0316	-0.0279
	(0.0097)	(0.0135)	(0.0122)	(0.0104)	(0.0141)	(0.0128)	(0.0175)	(0.0258)	(0.0194)
HOME_LISTENING	0.4887***	0.5054**	0.116	0.4683**	0.4473*	0.0658	0.2705	-0.5413	0.1127
	(0.1783)	(0.2398)	(0.2087)	(0.2047)	(0.2536)	(0.2157)	(0.7021)	(0.8358)	(0.5905)
HHI_HOMEMARKET	0.4536	0.7616	-0.3434	0.6724	0.9605	-0.2288	0.664	0.7846	-0.1111
	(0.3694)	(0.5192)	(0.3199)	(0.4287)	(0.5891)	(0.3530)	(0.4037)	(0.7128)	(0.6009)
LISTENERSHIP_ASYMMETRY	0.2463**	0.4173**	0.2221**	0.2608**	0.3788**	0.2068*	0.2143	0.3394*	0.2457
	(0.1007)	(0.1609)	(0.1017)	(0.1139)	(0.1783)	(0.1117)	(0.1667)	(0.2086)	(0.1368)
MEAN_QUANTITY	-0.0112	0.0176*	0.0028	-0.0098	-0.0183	-0.0012	0.021***	0.0156	0.0129
	(0.0076)	(0.0104)	(0.0078)	(0.0089)	(0.0523)	(0.0084)	(0.0062)	(0.0104)	(0.0111)
Dummies	None	None	None	None	None	None	None	None	None
Number of observations	104,349	70,386	121,898	104,349	70,386	121,898	104,349	70,386	121,898

Notes: 1. Standard errors in parentheses robust to heteroskedasiticty and clustered at the metro-market level
2. 2. Drivetime hours are 6:00am-9:59am & 3:00pm-6:59pm, daytime hours are 10:00am-2:59pm and night hours are 7:00pm-5:59am.
3. R^2 for between (within) regressions reflects the degree of between (within) market variation explained by the regressors.

Table 4.5(a): Market-Category Level Regressions with OVERLAP_MEASURE as Dependent Variable

	Pooled Cross-Section			Between Market-Hours			Within Market-Hours		
	(1) Drivetime	(2) Daytime	(3) Night	(4) Drivetime	(5) Daytime	(6) Night	(7) Drivetime	(8) Daytime	(9) Night
LN(NUMBER_STATIONS)	-0.1164 (0.0793)	-0.1556* (0.0924)	-0.1135* (0.0651)	-0.0231 (0.0707)	-0.0981 (0.0971)	-0.0751 (0.0672)	-0.1748 (0.1344)	-0.1222 (0.1300)	-0.0418 (0.0912)
LN(HOME_LISTENING)	0.4414** (0.1972)	0.4100* (0.2264)	0.2525 (0.2343)	0.1867 (0.1840)	0.2425 (0.1973)	0.0214 (0.2047)	0.4757 (0.4375)	0.5345 (0.4503)	0.5024* (0.2869)
HHI_HOMEMARKET	0.0189 (0.1405)	0.0567 (0.1704)	-0.0446 (0.1022)	0.1287 (0.1230)	0.0784 (0.1789)	-0.0221 (0.1028)	0.1607 (0.1846)	0.4036* (0.2412)	0.0729 (0.1446)
LISTENERSHIP_ASYMMETRY	0.2180** (0.0982)	0.2901** (0.1238)	0.0652 (0.0901)	0.1882** (0.0947)	0.3210** (0.1476)	0.0090 (0.0995)	0.2042 (0.1247)	0.3027** (0.1393)	0.0319 (0.0935)
LN(MEAN_QUANTITY)	0.0166 (0.0501)	0.0229 (0.0537)	-0.0556* (0.0275)	-0.0390 (0.0855)	0.1371 (0.1245)	-0.0297 (0.0488)	0.0505* (0.0296)	0.0059 (0.0334)	-0.0405** (0.0183)
QUANTITY_ASYMMETRY	0.0210 (0.0868)	-0.0028 (0.0986)	0.0311 (0.0432)	-0.5752 (0.2408)*	-0.3817 (0.4088)	-0.0722 (0.2050)	0.1257** (0.0569)	0.0344 (0.0678)	0.0296 (0.0298)
Dummies	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Market-Category	Hour Week Day Market-Category	Hour Week Day Market-Category
R^2 (including dummies)	0.0050	0.0068	0.0048	0.0753	0.0750	0.0806	0.0018	0.0024	0.0021
Number of observations	125,851	112,886	177,237	125,851	112,886	177,237	125,851	112,886	177,237

Notes: 1. Standard errors in parentheses robust to heteroskedasiticty and clustered at the metro-market-category level.
2. 2. Drivetime hours are 6:00am-9:59am & 3:00pm-6:59pm, daytime hours are 10:00am-2:59pm and night hours are 7:00pm-5:59am.
3. R^2 for between (within) regressions reflects the degree of between (within) market variation explained by the regressors.

Table 4.5(b): Market-Category Level Regressions with OVERLAP_MEASURE as Dependent Variable Excluding the Largest 10 Metro-Markets

	Pooled Cross-Section			Between Market-Hours			Within Market-Hours		
	(1) Drivetime	(2) Daytime	(3) Night	(4) Drivetime	(5) Daytime	(6) Night	(7) Drivetime	(8) Daytime	(9) Night
LN(NUMBER_STATIONS)	-0.1598** (0.0778)	-0.1930** (0.0965)	-0.1501** (0.0622)	-0.0725 (0.0709)	-0.1355 (0.1021)	-0.1105* (0.0654)	-0.1450 (0.1406)	-0.0862 (0.1356)	0.0303 (0.0991)
LN(HOME_LISTENING)	0.4206** (0.2134)	0.3885 (0.2491)	0.1799 (0.2695)	0.1913 (0.1919)	0.2498 (0.2129)	-0.0185 (0.2234)	0.4288 (0.4723)	0.5268 (0.5047)	0.4415 (0.2767)
HHI_HOMEMARKET	0.0961 (0.1479)	0.1131 (0.1645)	0.0096 (0.0913)	0.1842 (0.1308)	0.1229 (0.1823)	0.024 (0.1013)	0.2264 (0.1771)	0.5876*** (0.1939)	0.2053** (0.1037)
LISTENERSHIP_ASYMMETRY	0.2801*** (0.1042)	0.3716*** (0.1388)	0.0989 (0.0904)	0.2331** (0.0972)	0.3957** (0.1644)	0.0223 (0.0939)	0.2392* (0.1222)	0.3647** (0.1488)	0.0371 (0.1099)
LN(MEAN_QUANTITY)	0.0114 (0.0525)	0.0107 (0.0568)	-0.0682** (0.0285)	-0.0202 (0.0914)	0.151 (0.1351)	-0.0347 (0.0491)	0.0492 (0.0313)	0.0032 (0.0363)	-0.0463** (0.0201)
QUANTITY_ASYMMETRY	0.0408 (0.0975)	0.0027 (0.1093)	0.0612 (0.0439)	-0.5543** (0.2516)	-0.2572 (0.4451)	0.0399 (0.2045)	0.1523** (0.0622)	0.0359 (0.0759)	0.0312 (0.0325)
Dummies	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Market-Category	Hour Week Day Market-Category	Hour Week Day Market-Category
R^2 (including dummies)	0.0073	0.0112	0.0049	0.0863	0.0988	0.0976	0..0017	0.0033	0.0013
Number of observations	106,061	94,108	146,605	106,061	94,108	146,605	106,061	94,108	146,605

Notes: 1. Standard errors in parentheses robust to heteroskedasiticty and clustered at the metro-market-category level.
2. 2. Drivetime hours are 6:00am-9:59am & 3:00pm-6:59pm, daytime hours are 10:00am-2:59pm and night hours are 7:00pm-5:59am.
3. R^2 for between (within) regressions reflects the degree of between (within) market variation explained by the regressors.

Table 4.5(c): Market-Category Quantile Regressions with OVERLAP_MEASURE as Dependent Variable Between Market-Hour Formulation

	Drivetime			Daytime			Night		
	(1) 10th	(2) 90th	(3) Range 90th-10th	(4) 10th	(5) 90th	(6) Range 90th-10th	(7) 10th	(8) 90th	(9) Range 90th-10th
LN(NUMBER_STATIONS)	0.0913 (0.0913)	-0.1779 (0.1412)	-0.2692* (0.1493)	0.0484 (0.1563)	-0.2320 0.1842	-0.2805 0.2121	0.0917 0.0850	-0.1941 0.1247	-0.2858* (0.1557)
LN(HOME_LISTENING)	-0.2368 (0.2429)	0.1841 (0.2081)	0.4209 (0.3430)	-0.1315 (0.1787)	0.5565 0.3813	0.6881* 0.3718	0.2758 0.3203	-0.1208 0.4117	-0.1484 0.4077
HHI_HOMEMARKET	-0.0328 0.2122	0.2198 (0.2164)	0.2526 (0.2795)	-0.0063 (0.2766)	0.3934 0.3481	0.3997 0.3917	0.0126 0.1461	0.0248 0.1560	0.0122 (0.1787)
LISTENERSHIP_ASYMMETRY	0.0985 0.1401	0.3667** (0.1815)	0.2682 (0.2493)	0.4643 (0.1835)	0.5372* 0.2670	0.0729 (0.2442)	-0.0187 0.1000	0.2268 0.2163	0.2455 (0.2271)
LN(MEAN_QUANTITY)	-0.2032* 0.1100	-0.0612 (0.1438)	0.1421 (0.1738)	-0.0403 (0.1833)	-0.0887 0.2678	-0.0484 0.3270	-0.1321 0.0569	0.0155 0.1052	0.1476 (0.0991)
QUANTITY_ASYMMETRY	-0.1666 0.3023	-1.6082*** (0.4224)	-1.4415*** (0.4436)	-0.1762 (0.5554)	-1.5243** 0.7673	-1.3481 0.8237	0.2224 0.2887	-0.5998* 0.2746	-0.8222** (0.3380)
Dummies	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Category	Hour Week Day Market-Category	Hour Week Day Market-Category	Hour Week Day Market-Category
Number of observations	125,851	125,851	125,851	112,886	112,886	112,886	177,237	177,237	177,237

Notes: 1. Standard errors in parentheses robust to heteroskedasiticty and clustered at the metro-market-category level
2. 2. Drivetime hours are 6:00am-9:59am & 3:00pm-6:59pm, daytime hours are 10:00am-2:59pm and night hours are 7:00pm-5:59am.
3. R^2 for between (within) regressions reflects the degree of between (within) market variation explained by the regressors.

Table 4.6: Pair Regressions with PAIR_OVERLAP_MEASURE as Dependent Variable

	Pooled Cross-Section			Between Pairs			Within Market-Hour-Days		
	(1) Drivetime	(2) Daytime	(3) Night	(4) Drivetime	(5) Daytime	(6) Night	(7) Drivetime	(8) Daytime	(9) Night
SAME_CATEGORY	0.0286	0.0457	-0.0281	0.0399	0.0431	0.0034	0.0226	0.0474	-0.0295
	(0.0384)	(0.0398)	(0.0230)	(0.0441)	(0.0420)	(0.0292)	(0.0380)	(0.0404)	(0.0228)
SAME_OWNER	0.0159	0.021	0.0078	0.0084	0.0155	0.0069	0.0112	0.0171	0.0087
	(0.0161)	(0.0170)	(0.0116)	(0.0122)	(0.0152)	(0.0103)	(0.0167)	(0.0171)	(0.0116)
SAME_CATEGORYOWNER	-0.0628	-0.0692	-0.0554	-0.0614	-0.0455	-0.0597**	-0.0534	-0.0611	-0.0556*
	(0.0445)	(0.0502)	(0.0337)	(0.0385)	(0.0449)	(0.0296)	(0.0471)	(0.0502)	(0.0326)
QUANTITY_ASYMMETRY	-0.0003	-0.0008	-0.0007	-0.0093***	-0.0067	-0.0012	-0.0012	-0.0019	-0.0015
	(0.0013)	(0.0016)	(0.0008)	(0.0022)	(0.0053)	(0.0027)	(0.0015)	(0.0016)	(0.0009)
MEAN_QUANTITY	-0.0033*	-0.0048*	-0.0047***	-0.0049**	-0.0067	-0.0082**	-0.0013	0.0000	-0.0012
	(0.0018)	(0.0026)	(0.0018)	(0.0025)	(0.0053)	(0.0031)	(0.0023)	(0.0028)	(0.0017)
MEAN_LISTENERSHIP	0.0236	0.0379*	0.0338**	0.0124	0.0215	0.0309	-0.0109	-0.0086	0.0144
	(0.0188)	(0.0214)	(0.0166)	(0.0180)	(0.0255)	(0.0180)	(0.0208)	(0.0223)	(0.0182)
LISTENERSHIP_ASYMMETRY	0.0082	0.0006	-0.0112	0.0050	0.0015	-0.0124	-0.0006	-0.003	-0.0133
	(0.0141)	(0.0153)	(0.0107)	(0.0123)	(0.0171)	(0.0122)	(0.0151)	(0.0155)	(0.0114)
CLOSE_FREQUENCY	0.0048	0.0041	0.0092	0.0060	0.0152	0.0050	-0.0043	-0.0076	0.0034
	(0.0128)	(0.0133)	(0.0105)	(0.0115)	(0.0131)	(0.0096)	(0.0124)	(0.0122)	(0.0108)
CATEGORY_CLOSEFREQUENCY	-0.0169	-0.0234	0.0117	-0.0518	-0.0374	-0.0080	-0.0065	-0.0219	0.0174
	(0.0423)	(0.0427)	(0.0244)	(0.0469)	(0.0463)	(0.0300)	(0.0413)	(0.0420)	(0.0241)
Dummies	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day	Hour Week Day	Market-Day-Hour	Market-Day-Hour	Market-Day-Hour
R^2 (including dummies)	0.0005	0.0007	0.0009	0.0104	0.0134	0.0103	0.0001	0.0002	0.0003
Number of observations	1,120,786	1,075,633	1,937,076	1,120,786	1,075,633	1,937,076	1,120,786	1,075,633	1,937,076

Notes: 1. Standard errors in parentheses robust to heteroskedasiticty and clustered at the metro-market level.
2. Drivetime hours are 6:00am-9:59am & 3:00pm-6:59pm, daytime hours are 10:00am-2:59pm and night hours are 7:00pm-5:59am.
3. Regressions run on a sample of pairs from each market: sample includes all pairs home to the same category or which are ever commonly owned and a 50% sample of remaining pairs
3. R^2 for between (within) regressions reflects the degree of between (within) pairt variation explained by the regressors.