The Strategic Timing Incentives of Commercial Radio Stations: An Empirical Analysis Using Multiple Equilibria

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Abstract

Commercial radio stations and advertisers may have conflicting interests about when commercial breaks should be played. This article estimates an incomplete information timing game to examine stations' equilibrium timing incentives. It shows how identification can be aided by the existence of multiple equilibria when appropriate data are available. It finds that stations want to play their commercials at the same time, suggesting that stations' incentives are at least partially aligned with the interests of advertisers, although equilibrium coordination is far from perfect. Coordination incentives are much stronger during drivetime hours, when more listeners switch stations, and in smaller markets.

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"Unfortunately for advertisers, not every broadcaster runs commercial blocks at exactly the same time. Therefore, the flipper hell-bent on commercial avoidance can always find an escape route. Broadcasters cooperating with each other to standardize commercial pod timing can cut off all flipper escape routes. Imagine the poor flipper; wherever he turns, horrors . . . a commercial! Once the flipper learns that there is no escape, he will capitulate and watch the advertising." (Gross (1988))

1 Introduction

This article estimates the strategic incentives of commercial radio stations deciding when to play their commercial breaks. The question of whether stations want to play their breaks at the same time (coordinate) or at different times (differentiate) is interesting because, while advertisers would almost certainly like stations to play their commercials at the same time, various features of the industry, such as the way in which station audiences are estimated, may make stations not want to do so. My empirical results, which show that in equilibrium stations do want to coordinate, indicate that mechanisms exist which at least partially align stations' incentives with the interests of advertisers.

Broadcast radio and television stations sell commercial time to advertisers and attract consumers by bundling commercials together with different types of programming. The ability of consumers to try to avoid commercials by switching stations in search of non-commercial programming presents a challenge to this business model and the evidence suggests that switching is quantitatively important. For example, Abernethy (1991) estimates that in-car listeners switch stations 29 times per hour on average and Dick and McDowell (2003) find that in-car listeners avoid more than half the commercials they would hear if they never switched stations. The above quotation argues that switching can be rendered ineffective if stations air commercials simultaneously. However, while advertisers would almost certainly like stations to reduce commercial avoidance[1], stations may have rather different incentives because prices are not based on how many people hear a particular commercial and even average commercial audiences are not measured. Instead, Arbitron, the radio ratings company, estimates a station's *average* audience (across both commercial and non-commercial programming)

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[1]Brydon (1994) argues that "for advertisers, the key point is this: if you can continue to listen to that for which you tuned in, why should you listen to a commercial break?". He suggests that stations should "transmit breaks at universally agreed uniform times. Why tune to other stations if ... they will be broadcasting commercials as well?".

and this may be maximized by playing commercials at different times to other stations.

A simple model captures these different incentives. Suppose that there are two commercial stations (A and B) and an outside option for listeners which never has commercial programming (e.g., NPR or a CD). There are two units of listeners. One unit has A as its preferred station (the "P1" in radio jargon) and one unit prefers B. There is an infinite sequence of odd and even time periods and each station has to choose between playing commercials in even periods or odd periods, playing music in the remainder. Listeners listen to their preferred station when it is playing music. When it plays commercials a proportion θ of these listeners switch to the other commercial station if it is playing music. If the other station also has commercials then θ' of listeners will switch to the outside option. If stations play commercials at the same time then the average audience of a commercial will be $1 - \theta'$ and a station's average audience (which is what Arbitron tries to measure) will be $\frac{2-\theta'}{2}$. On the other hand, if they play commercials at different times then these audiences will be $1 - \theta$ and 1 respectively, as a lower audience during a commercial is offset by a higher audience when the other station has a break. If $\theta > \theta'$, which is reasonable if commercial stations are closer substitutes with each other than with the outside option, then advertisers will want stations to play commercials at the same time while stations will not.

Of course, the market might find ways to align incentives.[2] For example, equilibrium prices should reflect the expected value of commercials to advertisers. However, any individual station may only have weak incentives to try to increase this expected value because the audience of its own commercials is not measured and market structure is fragmented (for example, in Spring 2008 15 different firms owned the 37 stations rated by Arbitron in the Chicago market). Alternatively, advertisers may be able to estimate the impact of their commercials on a particular station, even if they cannot measure their audience, by looking at how demand responds or by encouraging listeners to "call now". Even if this response does not affect revenues from the commercial in question, stations will care about it if it affects advertisers' willingness to pay for future spots.

I estimate stations' incentives using panel data on the timing of commercial breaks by 1,091 music

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[2] Contracts for radio advertising time do not specify the exact times at which commercials will run, presumably because it is very difficult for a station to guarantee a precise airing time in advance. This type of noise plays an important role in the game which I set out below.

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stations in 144 radio markets in 2001. The data is extracted from airplay logs which record, on a minute-by-minute basis, the music which stations play. Figure **??** shows the average proportion of stations playing commercials in each minute during two different hours of the day.

[FIGURE 1 HERE]

The distributions are far from uniform and indicate that stations tend to play commercials at the same time. However, we cannot infer from these aggregate patterns alone that stations want to coordinate on timing because they could also be explained by "common factors" making some parts of each hour particularly bad for commercials. Knowledge of the industry shows that common factors do affect timing decisions. For example, Arbitron estimates audiences based on how many people report listening to a station for at least five minutes during a quarter-hour (e.g. 4:30-4:45). Listeners who can be kept listening for ten minutes over a quarter-hour are therefore likely to count for two quarter-hours so stations avoid playing commercials, which would drive away listeners, at these times. They also avoid playing them at the beginning of each hour as many listeners switch on then and they are likely to switch stations immediately if they tune-in during a commercial.

How can strategic incentives be identified if these types of common factor are important? One approach would be to specify exclusion restrictions. For example, suppose that a station's own characteristics, such as its format, affect its timing preferences but do not directly affect the timing preferences of other stations. If there is variation in a station's competitors across markets (e.g., more Country stations in the south than in New England, and more Spanish stations in markets with large Hispanic populations) then strategic incentives could potentially be identified from how the timing decisions of stations in a particular format change as the formats of competitors vary.

Unfortunately I find that observable station characteristics have very little effect on timing choices, especially during drivetime hours, so that exclusion restrictions of this sort are unlikely to be useful. Instead I emphasize a more novel approach to identification which exploits the possible existence of multiple equilibria in the model and in the data. To see the intuition suppose that stations play a timing game with two alternative timing choices (1 and 2) which are equally attractive in terms of common factors (for example, neither is a quarter-hour). If stations want to coordinate then there

may be an equilibrium where stations cluster their commercials at time 1 and another equilibrium where they cluster their commercials at time 2. If some markets are in each equilibrium then the type of pattern that we would see in the data could look like Figure 2 which shows when stations in two markets played commercials during one particular hour. The distributions in both markets have three peaks, just like the aggregate distribution, but they are at noticeably different times.

[FIGURE 2 HERE]

If stations want to play commercials at different times then we would expect to observe excess dispersion within markets (market distributions less concentrated than the aggregate) rather than clustering. If there is no strategic incentive then, as long as common factors are the same across markets, there is no reason why we should observe either excess clustering or dispersion relative to the aggregate distribution. Therefore, if we observe stations clustering at different times in different markets and we can make some assumptions about how common factors vary across markets, then we may be able to infer that stations want to coordinate on timing.

The idea that multiple equilibria can aid identification is not entirely new: in particular, Brock and Durlauf (2001) make this argument in their analysis of non-linear peer effect models. The underlying structure of our models is very similar, but I develop my results in the context of estimating a game where the number of players is relatively small. In contrast, Brock and Durlauf consider settings with sufficiently many players that summary statistics on the actions of other players can simply be included as regressors in a single agent analysis. My approach - which raises some additional identification issues - is more naturally applicable in the type of oligopolistic market usually considered by IO economists.

The obvious concern with relying on multiple equilibria for identification of strategic incentives is that some forms of heterogeneity in common factors across markets could generate patterns which look like multiple equilibria. I show that controlling for observable heterogeneity and allowing for parametric forms of unobserved heterogeneity does not change my results. Perhaps more convincingly I also show that there are differences in the results across markets and hours which are consistent with coordination. For example, strategic incentives should be stronger when listeners are more likely to

switch stations. This is true during drivetime hours because in-car listeners, who are more numerous during drivetime, are closer to their dials/preset buttons.[3] Consistent with this, and with stations wanting to coordinate, I find greater clustering and estimate a stronger incentive to coordinate during drivetime than outside drivetime. I also find that there is greater coordination in smaller markets, which typically have fewer stations, which is consistent with some models of listener behavior.

The article is organized as follows. The rest of the introduction reviews the related literature. Section 2 describes the data. Section 3 presents the model of the timing game. Sections 4 and 5 discuss identification and estimation. Section 6 presents the empirical results, Section 7 provides a discussion of the strength of coordination and the role of multiple equilibria and Section 8 concludes.

Related Literature

The observation that radio and TV stations tend to play commercials at the same time has motivated a small theoretical literature. Epstein (1998), Zhou (2000) and Kadlec (2001) assume that stations try to maximize the audience of commercials and show that in equilibrium stations play commercials at the same time. Sweeting (2006) provides theoretical models where strategic incentives should lead the degree to which commercials overlap in equilibrium to vary with the propensity of listeners to switch stations, which varies across hours, and market characteristics, such as the number of stations, ownership concentration and asymmetries in station listenership, together with some supporting reduced form evidence. I provide further evidence for these differences in the current article, which comes out of the estimation of a more formal timing game.

I model stations as playing an incomplete information game. The incomplete information assumption has typically been used for convenience when there are many players, many actions or strategies are likely to be complicated (e.g., Seim (2006), Ellickson and Misra (2007), Augureau et al. (2006) and the recent literature on dynamic games). In my setting stations make timing choices simultaneously in real-time so incomplete information is more plausible. Bajari et al. (2007b, hereafter BHNK) discuss identification in incomplete information games, noting the current article's contribution with

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[3]A 1994 survey (discussed in MacFarland (1997)) found that 70% of in-car listeners switch at least once during a commercial break compared with 41% of at home and 29% of at work listeners. Arbitron's Fall 2001 Listening Trends survey estimated that 39.2% of drivetime listening is in-car compared with 27% or less at other times of the day.

respect to multiple equilibria. I use two common estimation procedures: a computationally light two-step approach (e.g., BHNK) and the Nested Fixed Point algorithm (NFXP, Rust (1987)). In both cases, I assume that each station is using the same strategy every time it is observed in the data, and I provide three tests which support this assumption. These tests also show that there is no evidence of multiple equilibria *within markets*, and support the assumption of imperfect information.

Multiple equilibria have received more attention in games of complete information. I borrow from several articles in this literature (Bajari et al. (2007a), Bjorn and Vuong (1985), Ackerberg and Gowrisankaran (2006), Tamer (2003)) when specifying an equilibrium selection mechanism to close the model. Several recent articles, including Ciliberto and Tamer (2007) and Pakes et al. (2006), have shown that it may be possible to bound the parameters without specifying a selection mechanism. This is not true in my setting and, furthermore, the emphasis in the current article is different because I argue that the existence of multiple equilibria can in itself help to identify the payoff parameters.

2   Data

The data on the timing of commercials are extracted from airplay logs collected by Mediabase 24/7, a company which uses electronic technologies to collect data on music airplay.

Coverage of the Mediabase Sample

I use logs from the first five weekdays of each month in 2001 for 1,091 music stations, including stations in the Adult Contemporary, Contemporary Hit Radio/Top 40, Country, Oldies, Rock and Urban formats as defined by BIAfn's *MediaAccess Pro* database.[4]   This database is also used to allocate stations to 144 markets, including all of the largest radio markets in the US with the exception of Puerto Rico.[5]   Although some stations have listeners in multiple markets (e.g., Boston and Providence, RI), most of a station's listenership is in its market of license and I treat music stations licensed to a

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[4]I combine stations in the Album Oriented Rock and Rock formats as stations in these formats play relatively similar music and seem to make similar timing choices.   I drop observations for two station-quarters where BIAfn does not classify the station into one of these six formats.

[5]I drop observations from three markets (each with only one station) which enter the data only in December 2001. These stations were used in earlier versions of the paper without significant effects on the results.

market as players in the timing game.

[TABLE 1 HERE]

Unfortunately, the Mediabase sample does not cover include every licensed music station. Table 1 summarizes the coverage of the sample, splitting markets into two groups based on market size. In large markets, the sample includes over 70% of stations, and they account for over 86% of music station listenership because Mediabase concentrates on larger stations. The sample contains a smaller proportion of stations in smaller markets but it still includes two-thirds of music listenership. The panel is unbalanced over time, both because the Mediabase sample expands during the year and some logs for individual station-days are missing. Overall there are 51,601 station-days of data, with up to 59 days per station. The issues which missing data create for estimation are discussed in Section 5.

Airplay Logs

[TABLE 2 HERE]

Table 2 shows an extract from an airplay log. The log lists the start time of each song and indicates whether there was a commercial break between songs. I estimate whether any particular minute has a commercial break using the following procedure:

1. the length of each song is estimated by the median time between songs with no commercials;[6]

2. a minute-by-minute schedule for each station-hour is created assuming that each song is played its full length unless this would erase a commercial break or overlap the start of the next song; and,

3. if the resulting breaks are more than five minutes long (a plausible maximum length), the break is shortened to five minutes by sequentially taking minutes from the end and then the start of the break. This procedure increases the possibility of measurement error, so I drop station-hours with fewer than 8 songs as measurement errors are more likely when more time is unaccounted

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[6]If a song is played less than 10 times without being followed by a commercial break, I asssume that the song is four minutes long, the median length of all songs.

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for. In general measurement error, as long as it is not correlated among the stations in a market, is likely to lead to strategic incentives being understated.

Definition of Timing Choices

In common with the existing literature I specify a discrete choice game to estimate stations' strategic incentives. To do this, I need to specify a small number of timing options which stations will choose between. As the end of the hour has the most commercials, I classify stations into three groups: stations which are playing commercials at 50 minutes past the hour, stations which are playing commercials at 55 minutes past the hour and stations which are playing them at neither of these times. As I will show in Section 5, I can make assumptions under which it is consistent to simplify the game in this way. A complication arises if a station has commercials at both :50 and :55 (possible if the station has a short song between two breaks) but as I will show in a moment only a few station-hours have this feature and, for simplicity, I simply exclude them from the rest of the analysis.

Although I have data from every hour of the day I focus the analysis on four hours. 4-5 pm and 5-6 pm are two hours in the middle of the afternoon drivetime period when many listeners will be in their cars and any strategic incentives should be quite strong. I focus on the afternoon drive because in the morning many stations have primarily talk programming and, because this leaves a lot of time which is unaccounted for in the log, it is difficult for me to locate commercials precisely: between 7 and 9 am more than 50% of station-hours fail to meet the 8 song criterion whereas less than 3% of station-hours do so in the afternoon. I use 12-1 am and 9-10 pm as two representative non-drivetime hours, although results look similar for several others which I have tried.

[TABLE 3 HERE]

Table 3 shows the number of station-hours with commercials in each of the three slots, and the number which have commercials at both :50 and :55. This latter number is always small, so that dropping these station-hours should not introduce major biases. In every hour, between 50 and 60% of the remaining stations are playing commercials at either :50 or :55. Table 4 shows that timing

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choices vary relatively little across formats for 12-1 pm and (especially) 4-5 pm. This is significant because a standard way to identify strategic incentives would be to use variation in timing preferences across formats and plausibly exogenous variation in the format mix of stations across markets.

[TABLE 4 HERE]

Observable Station and Market Characteristics

In several specifications I allow for observable variables to affect either stations' non-strategic timing preferences or the strength of strategic incentives. Format dummies classify the programming of each station, with the Rock format having the most stations (323). I define two dummies for stations owned by the largest radio companies, Clear Channel and Infinity. 310 (118) stations are owned by Clear Channel (Infinity) at some point during the year. Two variables describe commuting patterns based on data from the 2001 US Census: the average commute time (mean 26 minutes) and the average time at which people leave home for work in the morning (mean 7:24 am). Unfortunately evening commute data, which would be more relevant for the analysis, are not available. Market rank is an ordinal measure of market size based on 2001 population (1=New York City, 144=Muskegon, MI). A station's share is its share of music station listenership (averaged over the Spring and Fall quarters in 2001). The average share is 0.10. Ownership HHI is based on the ownership of music stations in the market, where each station is weighted equally (not by listenership). The median ownership HHI is 0.29. A listenership asymmetry variable reflects the distribution of listenership across stations and it equals the sum of squared listenership shares divided by the number of stations, so it has a minimum value of 1 when all shares are equal. Its median value is 1.23. The share, ownership HHI and listenership asymmetry variables are calculated using all music stations in the market which have enough listeners to be rated by Arbitron whether or not they are monitored by Mediabase. The HHI and asymmetry variables tend to be larger in smaller markets (the correlations with market rank are 0.38 and 0.35 respectively).

3 An Incomplete Information Timing Game

This section develops the incomplete information game used to model stations' timing decisions.

Payoff Function

There are N_m ($i = 1, ..., N_m$) stations in market m ($m = 1, ..., M$) and each station chooses one of T possible timing choices ($t = 1, ..., T$). As every market has more than one music station I assume that $N_m \geq 2$ even though there are some markets where only one station's timing choices are observed. Station i's payoff from choosing action t is

$$\pi_{imt} = X_{im}\beta_t + \alpha P_{-imt} + \varepsilon_{imt} \tag{1}$$

where P_{-imt} is the proportion of other stations in the market choosing action t. This payoff function is a "reduced form" in the sense that neither listener or advertiser behavior are modelled. The first term ($X_{im}\beta_t$) allows timing choices to have different average payoffs (e.g., lower for quarter-hours) and for station and market characteristics to affect timing preferences. The coefficient on the constant would reflect the value of common factors which are the same across stations and markets. As usual for a discrete choice model, the optimal action will reflect a cutoff rule so that not all of the βs are identified, so I normalize $\beta_1 = 0$. Stations are *identical* if they do not differ in payoff-relevant characteristics (i.e., there are no station-specific Xs).

The second term (αP_{-imt}) determines the strategic interactions which are the focus of this article. α will be positive if stations want to play commercials at the same time. I assume that there are no strategic interactions across markets and that α is the same across actions. The formulation here also assumes that α is the same across markets, but this will be relaxed in some of the empirical specifications.

The final term (ε_{imt}) is a random shock to a station's payoff from making a particular timing choice. I assume that ε_{imt} is *private information* to station i so that the game is one of incomplete information. To guarantee the existence of a pure strategy Bayesian Nash equilibrium and to derive

my identification results I assume that the εs are drawn from a continuous distribution and that they are iid across stations and actions. The interpretation of the εs in my setting is that on any particular day a station has to fit commercial breaks around other pieces of programming (songs, competitions, weather updates) in real time and, because it would annoy listeners to cut these types of programming off, this creates some uncertainty about when commercials will be played.[7] The private information assumption will be reasonable if this uncertainty is resolved in ways which are hard for other stations to predict. In some of the empirical specifications I will also allow for a persistent station-specific component of preferences (drawn from a parametric distribution) which is *known by all stations* but not the econometrician, and I show that once I allow for this the data is consistent with the time-varying component of the error being both iid and private information. In taking the model to data I assume that the εs are drawn from a Type I extreme value distribution. This parametric distribution is particularly useful because it allows me to estimate α using a subset of choices.

Station Strategies and Bayesian Nash Equilibria

I assume that stations use static Bayesian Nash equilibrium strategies. This assumption is restrictive because a richer set of equilibria may be supported as timing decisions are made repeatedly. However, in Section 6 I find no evidence of significant dynamics, in the sense of a station's timing decisions *changing* in response to the actions of its competitors. One interpretation of this pattern is that any dynamics which led the stations to a stable equilibrium would have taken place in the years prior to my data.

A station will choose the action which maximizes its expected payoffs given the strategies of other stations, i.e., action t will be chosen if and only if

$$\Pi_{imt}(X_{im}, \sigma_{-imt}, (\alpha, \beta_t)) - \Pi_{imt'}(X_{im}, \sigma_{-imt'}, (\alpha, \beta_{t'})) \geq \varepsilon_{imt'} - \varepsilon_{imt} \quad \forall t' \neq t \tag{2}$$

$$\text{where } \Pi_{imt}(X_{im}, \sigma_{-imt}, (\alpha, \beta_t)) = X_{im}\beta_t + \alpha \frac{\sum_{j \neq i} \sigma_{jmt}}{N_m - 1}$$

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[7]Scheduling software could be used to reduce this uncertainty but experienced DJ are typically given discretion to create programming which appeals to listeners. Warren (2001) and Gross (1988) describe how the difficulties of consistently playing commercials at precise times limit the degree of coordination.

and σ_{jmt} is the probability that station j chooses action t before the εs are realized and from the perspective of other stations who do not observe the ε_js. The choice probabilities implied by these choice rules are the most convenient way to represent strategies. It is also useful to define Π_{im} as the vector of differences between Π_{imt} and Π_{im1} for actions $t = 2, .., T$

$$\Pi_{im}(X_{im}, \sigma_{-im}, \alpha, \beta) = \begin{pmatrix} \Pi_{im2}(X_{im}, \sigma_{-im2}, (\alpha, \beta_2)) - \Pi_{im1}(\sigma_{-im1}, \alpha) \\ ... \\ \Pi_{imT}(X_{im}, \sigma_{-imT}, (\alpha, \beta_T)) - \Pi_{im1}(\sigma_{-im1}, \alpha) \end{pmatrix} \qquad (3)$$

The best response function $\sigma_{im} = \Gamma(\Pi_{im}(X_{im}, \sigma_{-im}, \alpha, \beta))$ maps from $\Pi_{im}(X_{im}, \sigma_{-im}, \alpha, \beta)$ into i's choice probabilities. The exact form of Γ depends on the distribution assumed for the εs. In a Bayesian Nash equilibrium every station's strategy is a best response, so that $\sigma_{im}^* = \Gamma(\Pi_{im}(X_{im}, \sigma_{-im}^*, \alpha, \beta))$ $\forall i$. A Bayesian Nash equilibrium is *symmetric* if all stations with the same characteristics have the same strategies. If $\alpha \geq 0$ then it is easy to show that all equilibria will be symmetric. If $\alpha < 0$ then there may be asymmetric equilibria but it is easy to show that, for given parameters, strategies must tend towards being symmetric as the number of stations increases.[8]

[FIGURE 3 HERE]

As the εs are drawn from a continuous distribution Brouwer's fixed point theorem guarantees the existence of at least one equilibrium. The number of equilibria can vary with the parameters. As an illustration suppose that there are two stations (i and j), two actions (1 and 2), the εs are distributed iid Type I extreme value (logit) and $X_j \beta_2 = 0$. Figure 3 shows their reaction functions for four different cases, where $i(j)$'s best response is on the vertical (horizontal) axis. In all cases $X_i \beta_2 = 0.1$ so i has a preference for choosing action 2, and there is an equilibrium wherever the reaction functions cross.

In panels (a) and (b) $\alpha > 0$ so stations want to choose the same times for commercials and their reaction functions slope upwards. In panel (a) $\alpha = 1$. If i knew that j was going to choose action 2 for

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[8] The intuition is simple: as N_m increases $\frac{\sum_{j \neq i} \sigma_{-imt}}{N_m - 1}$ will look increasingly similar from the perspective of any two stations who will therefore have increasingly similar best response strategies.

sure then i would choose action 2 with probability 0.75. On the other hand if i knew that j was going to choose action 1 it would choose action 2 with a much lower probability (0.29). The coordination incentive is therefore quite strong in the sense that each station's strategy is quite sensitive to the strategy of the other station. However, in equilibrium coordination is very modest: i chooses action 2 with probability 0.533 and j chooses action 2 with probability 0.517, so that the probability that they play their break at the same time is 0.501, only 0.2% greater than it would be if $\alpha = 0$. Weak coordination in equilibrium reflects the existence of an externality in the timing game: each station ignores how its timing decision affects the payoff (audience) of the other station.

α is larger in panel (b) and there are three equilibria, which is the maximum number when there are two actions, $\alpha > 0$ and the εs are drawn from a bell-shaped distribution like the logit for any number of stations (Brock and Durlauf (2001)).[9] The middle equilibrium (where $\sigma_{i2}^* = 0.441, \sigma_{j2}^* = 0.439$) is unstable in the sense that the application of iterated best responses close to this equilibrium would lead away from this equilibrium. The other equilibria, which are stable, involve more coordination and the action which stations coordinate on differs across the equilibria. In solving the model I assume that only stable equilibria are played because they are much easier to find. If $\alpha > 0$ a stable equilibrium will always exist (Brock and Durlauf (2001), Proposition 4), which my two-step results - which do not require me to solve for an equilibrium - indicate is the empirically relevant case. In practice I have been able to find a stable equilibrium for any value of α. If i's preference for action 2 was increased then its reaction function would shift upwards and only the equilibrium involving coordination on action 2 would survive. This is consistent with the common intuition (e.g., Augureau et al. (2006)) that multiple equilibria cannot be supported when players differ substantially in characteristics affecting non-strategic preferences. I show that observable characteristics have little impact on timing choices in my setting, especially during drivetime hours, which makes it more plausible that multiple equilibria might exist.

In panels (c) and (d) $\alpha < 0$ so stations want to choose different times for commercials. Once again when the strategic incentives are strong there are three equilibria, but this time they involve stations tending to choose different actions.

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[9] If $\alpha < 0$ then there are a maximum of three equilibria when there are two stations.

Equilibrium Selection

The possible existence of multiple equilibria requires the specification of an "equilibrium selection mechanism" to make predictions about what will be chosen or to calculate the likelihood of a particular outcome. Specifically I assume that if there are E possible equilibria, equilibrium e is played with probability λ_e, $\sum_{e=1}^{E} \lambda_e = 1$.

The selection mechanism can be thought about in two different ways. First, there could be some real payoff-independent randomization device which leads to stations coordinating on particular equilibrium strategies. Second, it can act as a statistical construct which describes the proportion of markets in each equilibrium. No additional restrictions are imposed if λ_e is conditioned on station and market characteristics.

In taking the model to data I make the additional assumptions that only stable equilibria are played (so $\lambda_e = 0$ for non-stable equilibria) and that the equilibrium played in a particular market does not change during the one year period of my data. I show that the second assumption is consistent with the data. With this assumption and a sufficiently long panel the payoff parameters are identified and can be estimated without explicit estimation of the equilibrium selection mechanism. As I only have a medium length panel (a maximum of 59 days per station) I also present results where the selection mechanism is estimated. In this case I treat λ_e as a constant, rather than as a function of market characteristics, in order to reduce the computational burden.[10]

4 Identification

The data consists of observable characteristics and, as outcomes, the timing choice of each station. The parameters are identified if and only if a unique set of parameters gives rise to any set of probabilities for each outcome. I separate the discussion into two parts: first, the assumptions under which the payoff parameters are identified if the equilibrium choice probabilities of each station are known and second, the conditions under which equilibrium choice probabilities can be identified from the data.

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[10]Earlier versions of this paper included models with market-specific λs and λs which varied with observed market characteristics including the number of stations. Bajari et al. (2007a) estimate a model where λ depends on the properties of the equilibrium itself (e.g., joint payoff-maximizing).

Identification of Payoff Parameters Given Equilibrium Choice Probabilities

Previous studies of identification in discrete choice incomplete information games (BHNK, Pesendorfer and Schmidt-Dengler (2007)) assume that the researcher observes the equilibrium strategies for each station (σ_{im}^*) and that a single equilibrium is played. I now show that if equilibrium strategies are known then multiple equilibria will provide additional identification of the payoff parameters. Throughout I assume that $\beta_1 = 0$, the εs are iid draws from a known, continuous distribution and T (the number of actions) is the same across actions. To keep the presentation simple I also assume that N (the number of stations) is the same across markets and is weakly greater than 2, as there are no monopoly markets in my data.[11] The results generalize to the case where N_m differs across markets. A useful result, shown by Hotz and Miller (1993), is that the Γ function, which maps differences in choice specific value functions to optimal choice probabilities, can be inverted so that for each distinct set of equilibrium choice probabilities there are $T-1$ linearly independent equations of the form

$$\Gamma^{-1}(\sigma_{im}^*) = X_{im}\beta_t + \alpha \left(\frac{\sum_{j \neq i} \sigma_{jmt} - \sum_{j \neq i} \sigma_{jm1}}{N-1} \right) \text{ for } t = 2, .., T \qquad (4)$$

Identical Stations

The helpful role of multiple equilibria can be seen most clearly when stations are identical (i.e., no station or market-specific Xs). In this case there are T payoff parameters $(\beta_2, ..., \beta_T, \alpha)$. The first identification result is negative.

Proposition 1 *If $N \geq 2$, stations are identical and a single symmetric equilibrium is played in every market then the parameters are not identified.*

Proof. If stations in all markets are identical and a single symmetric equilibrium is played then $\sigma_{imt}^* = \sigma_{-imt}^* = \sigma_{jnt}^* \; \forall i, j, m, n, t$ so that the strategies of each station yield an identical set of linear equations.[12] There are T parameters and $T-1$ linear equations so the parameters are not identified.

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[11] The existence of some monopoly markets would help identification because in these markets there would be no strategic incentive.

[12] The proportional formulation of the strategic incentive in the payoff function implies that symmetric equilibrium strategies will form equilibria in markets with any $N_m \geq 2$.

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In this case, not only are the parameters not point identified, but they can also not be bounded because for *any* α there exists a set of βs which can generate *any* set of equilibrium choice probabilities.

Proposition 2 *If stations are identical and at least two equilibria are played then the parameters are identified.*

Proof. One equilibrium provides $T-1$ linear equations. A second equilibrium must have at least two equilibrium choice probabilities which are different from the first, providing at least one additional linearly independent equation. Hence, the T parameters are identified. ∎

Additional equilibria would provide additional equations, so that the parameters will be overidentified. The logic of the proof also shows that the parameters will be identified with asymmetric equilibria, as there will be additional equations for each set of equilibrium choice probabilities, which in the asymmetric case will be different for different players.

Non-Identical Stations

If stations differ in observable characteristics which affect timing preferences then additional variation can identify the parameters. In particular, suppose that a station's own characteristics (e.g., format) affect its own timing preferences, that they do not directly affect the timing preferences of other stations and that there is exogenous variation in station characteristics of stations across markets (e.g., more Country stations in the south and in New England). In this case, variation in the characteristics of other stations in a market will create additional sets of equations like (4) as the $\sum_{j \neq i} \sigma_{jmt}$s will vary for given values of X_{im}.[13] Of course, multiple equilibria will still provide additional equations, and they may be particularly valuable when variation in station characteristics is limited (e.g., there are a few discrete types). The helpful role of multiple equilibria in this context is discussed by Brock and Durlauf (2001).

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[13]Variation in the set of station characteristics across markets, as well as variation within markets, is required. For example, with three types of station and one station of each type in every market a single equilibrium would produce $3(T-1)$ equations. However, there would be $3(T-1)+1$ parameters so the parameters would not be identified.

Identification of Equilibrium Choice Probabilities From Observed Outcomes

When a single symmetric equilibrium is played the identification of equilibrium choice probabilities is trivial because, with infinite data, they can be calculated by the frequency with which each action is chosen conditional on station and market characteristics. This is no longer true with multiple or asymmetric equilibria. However, the choice probabilities are still identified under certain conditions.

Panel Data and Equilibrium Assumptions

If it is assumed that each station is using the same strategy whenever it is observed in the data (strategies may differ across stations) and there is a long panel for each station, then each station's equilibrium choice probabilities can be calculated from its own choice frequencies without any pooling with other stations or markets. This argument forms the basis of my two-step estimation approach and I show in Section 6 that the assumption that the same strategy is used is consistent with the data.

Symmetric Equilibria and Identified Equilibrium Selection Mechanisms

With only cross-sectional data it is necessary to identify the mixture of equilibrium choice probabilities in the data including the λ parameters representing the equilibrium selection mechanism.[14] The data required for identification can be seen most clearly when there are two actions $(t = 1, 2)$, N identical stations in each market and equilibria are symmetric so that in any equilibrium every station is using the same strategy. If there are no more than E possible equilibria and in equilibrium e action 2 is chosen with probability σ_{e2}^* with this equilibrium played with probability λ_e then the probability that n_2 stations in a market choose action 2 is

$$\Pr(N_2 = n_2) = \sum_{e=1}^{E} \lambda_e \binom{N}{n_2} (\sigma_{e2}^*)^{n_2} (1 - \sigma_{e2}^*)^{N-n_2} \quad \sum_{e=1}^{E} \lambda_e = 1 \tag{5}$$

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[14]These argument can be made for either a cross-section of identical markets or one particular market where the equilibrium played varies over time.

This is the pmf of a binomial mixture model with E possible components. This model has $2E - 1$ parameters (E σ_{e2}^*s and $E - 1$ λ_es) and there are N linearly independent equations (5). Teicher (1963) shows that the parameters are identified if and only if $N \geq 2E - 1$.[15] The same condition holds with any number of actions ($T \geq 2$) because a multinomial model can always be broken down into a set of binomial models with stations choosing an action or its complement (see Kim (1984) and Elmore and Wang (2003) for formal results).

[FIGURE 4 HERE]

The intuition for the identification of a binomial mixture is that a mixture generates greater variance in the number of stations choosing a particular outcome than can be generated by a single binomial component. Figure 4(a) shows a hypothetical example. The black bars show the pmf for the number of stations choosing action 2 when there are two choices, $N = 8$, and there is a single symmetric equilibrium with identical stations and each station chooses action 2 with probability 0.5. The white bars show the pmf when there is an equal mixture of two symmetric equilibria. In the first equilibrium each station chooses action 2 with probability 0.6 and in the second equilibrium each station chooses action 2 with probability 0.4. The probabilities of outcomes with many stations choosing action 1 and outcomes with many stations choosing action 2 are both higher when there are multiple equilibria, even though the expected number of stations choosing each action is the same in both cases. Note that if stations want to choose different times for commercials and an asymmetric equilibrium is played then outcomes with many stations choosing the same action will have *lower* probability than could be generated by a single symmetric equilibrium. In this case, there will be too little variance in the number of stations choosing a particular action, rather than too much.

The remaining panels of Figure 4 show similar pictures constructed using data from 12-1 pm and 5-6 pm (as example drivetime and non-drivetime hours). The heavy lines show the distribution of the observed proportion of stations in a market-day-hour which play commercials at :55 out of the set of stations playing commercials at either :50 or :55. I condition in this way in order to make the figure comparable to (a), but I do take account of stations choosing neither of these actions when estimating

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[15]If N_m varies across markets then there must be a positive proportion of markets with at least $2E - 1$ stations.

the model. Panel (b) shows the distribution for all markets, and panel (c) shows the distribution for the smallest 74 markets (roughly breaking the dataset in half based on market size). For both size groups the density for 12-1 pm is more concentrated around 0.5 than the density for 5-6 pm, consistent with there being more clustering of commercials during drivetime. The thin solid lines show the expected density if a single symmetric equilibrium was played with each station choosing :55 with the probability that I observe it being chosen in the actual data. Even though this simple model ignores any observable differences across stations or markets which may affect timing choices, it fits the 12-1 pm data almost perfectly, with the actual density being within the 95% confidence intervals (dashed lines) along the whole interval. On the other hand, for 5-6 pm the distribution has greater variance than the single symmetric equilibrium model predicts. The difference is particularly clear in smaller markets, and this will be consistent with the results below where I find that incentives to coordinate are stronger and multiple equilibria are more common in smaller markets during drivetime.[16]

The statistical mixture model literature has not considered models which would correspond to ones in which stations differ in payoff-relevant observable characteristics. However, the previous logic shows that identification does not become more difficult in this case. Suppose that there are two actions and in every market there are the set of S observable types of station with N_s stations of type s using symmetric equilibrium choice probabilities σ_{es}^*. There are now $(S+1)E-1$ parameters ($S*E$ σ_{es}^*s and $E-1$ λ_es) and $\prod_{s=1}^{S}(N_s + 1) - 1$ observable probabilities

$$\Pr(N_{21} = n_{21}, .., N_{2S} = n_{2S}) = \sum_{e=1}^{E} \lambda_e \prod_{s=1}^{S} \binom{N_s}{n_{2s}} (\sigma_{es}^*)^{n_{1s}} (1 - \sigma_{es}^*)^{N-n_{1s}} \quad \sum_{e=1}^{E} \lambda_e = 1 \quad (6)$$

Identification still depends on having enough stations relative to the number of equilibria but notice that the number of observed probabilities (equations) increases *geometrically* in the number of types while the number of parameters increases only *linearly*. This implies, for example, that the equilibrium choice probabilities and the selection mechanism parameters are identified when markets have three

[16]Rysman and Greenstein (2005)'s Multinomial Test of Agglomeration and Dispersion (MTAD) can also be used to test the degree of clustering. It indicates significant clustering during drivetime hours using either binary choices (:50 or :55 conditional on one of these being chosen) or multinomial choices (:50, :55 or neither). There is weak evidence of clustering outside drivetime.

stations each of a different type and there are two equilibria.

5   Estimation

This section explains the estimation strategy.   I begin my explaining how I can estimate strategic

incentives using only a subset of choices, before describing two different estimation procedures.

Estimation Using A Subset of Choices

Stations can play several sets of commercials at many different times during an hour.   Estimation

of a game with many possible choices, multiple equilibria and observed and possibly unobserved

heterogeneity is well beyond the current literature.   However, if the εs are distributed Type I extreme

value then the strategic incentive can be estimated using only information on whether commercials

are being played at two particular times (:50 or :55 past the hour), exploiting a well-known feature of

the logit that only a subset of choices are required.   Labelling these timing choices 1 and 2 $(\beta_1 = 0)$

the probability that station i chooses action 2 from the full set of T possible actions is

$$\sigma^*_{im2} = \frac{\exp\left(X_{im}\beta_2 + \alpha\frac{\sum_{j\neq i}\sigma^*_{jm2}}{N_m-1}\right)}{\sum_{t=1}^{T}\exp\left(X_{im}\beta_t + \alpha\frac{\sum_{j\neq i}\sigma^*_{jmt}}{N_m-1}\right)} \tag{7}$$

The probability of action 2 being chosen *conditional* on either action 1 or action 2 being chosen

$\left(\sigma^*_{im(2|1 \text{ or } 2)}\right)$ is

$$\sigma^*_{im(2|1 \text{ or } 2)} = \frac{\exp\left(X_{im}\beta_2 + \alpha\left(\frac{\sum_{j\neq i}(2\sigma^*_{jm(2|1 \text{ or } 2)}-1)\sigma^*_{jm(1 \text{ or } 2)}}{N_m-1}\right)\right)}{1 + \exp\left(X_{im}\beta_2 + \alpha\left(\frac{\sum_{j\neq i}(2\sigma^*_{jm(2|1 \text{ or } 2)}-1)\sigma^*_{jm(1 \text{ or } 2)}}{N_m-1}\right)\right)} \tag{8}$$

where $\sigma^*_{jm(1 \text{ or } 2)}$ is the probability that station j chooses action 1 or action 2. β_2 and α can be

consistently estimated using the conditional choice probabilities in (8) as long as I adjust appropriately

for the probabilities that one of these choices is made by other stations $(\sigma^*_{jm(1 \text{ or } 2)})$ which can be

21

estimated.[17]   An advantage of using (8), rather than (7), in estimation is that it does not require knowledge of whether stations tend to make the same or different timing choices when they choose neither action 1 nor action 2.

Variation in the proportion of stations choosing actions 1 or 2 across markets can also help to identify α. The intuition is straightforward. If $\alpha > 0$ then the incentive of a station playing an ad at :50 or :55 to try to coordinate with other stations increases in the probability that other stations will be having commercials then. The data is consistent with this story: in all hours there is a positive correlation between (i) the probability that two stations playing commercials at :50 and :55 have their ads at the same time and (ii) the proportion of other stations in the market that have commercials at either one of these times.[18]   The correlation is statistically significant at the 1% level for both drivetime hours in smaller markets. Possible sources of variation in the number of stations playing commercials at :50 or :55 include multiple equilibria in the full timing game (e.g., so that stations coordinate on having commercials earlier in the hour), variation in the number of blocks of commercials that stations have during an hour and/or variation in the demand for commercial time across stations and markets.

Two Step Estimation

The two step estimation approach follows the panel data identification argument set out above. If a particular station j uses the same strategy throughout my data then its equilibrium choice probabilities can be estimated by

$$\widehat{\sigma_{jmt}} = \frac{\sum_{d=1}^{D_{jm}} I_{jdmt}}{D_{jm}} \tag{9}$$

where I_{jdmt} is equal to 1 if it chooses action t on day d and D_{jm} is the number of days that it is observed in the data. These estimates can be used to calculate the terms in the inner brackets on

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[17]Specifying binary choices of "action 2" or "not action 2" does not simplify the problem because the probability of choosing action 2 is given by (7) which depends on all of the parameters. Intuitively, the additional parameters are required because without them one cannot tell how much coordination there is when "not action 2" is chosen.

[18]The correlations were calculated by regressing a dummy for whether two stations playing commercials at :50 or :55 have them at the same time on the proportion of other stations in the market playing commercials at either of these times and a constant. The correlations are positive in all hours. When an interaction with market rank is included, the interaction is significant at the 0.1% level in both drivetime hours.

the right-hand side of (8), and a binomial logit model can then be used to estimate β_2 and α. As there are missing observations for some stations, it is necessary to assume that these are not related to timing choices. Stations which are not monitored by Mediabase are ignored entirely. Standard errors are calculated using a block bootstrap where markets are resampled.

Nested Fixed Point Estimation (NFXP)

The NFXP method requires solving for equilibrium strategies for many values of the parameters. I provide an overview here, focusing on the simplest specification (Model 1 below). The details are provided in the Appendix. The estimation technique is Simulated Maximum Likelihood (SML)[19] and, as mentioned above, I assume that each station is using the same strategy whenever it is in the data although this strategy may differ across stations. This also implies that if there are multiple equilibria, the equilibrium played in a particular market does not change over time.

Equation (8) describes the equilibrium conditional choice probabilities for choosing :50 or :55 as a function of β_2, α and the probabilities with which each station has a commercial at one of these times. I model these latter probabilities as

$$\sigma^*_{im(1 \text{ or } 2)} = \frac{\exp(\beta_{1 \text{ or } 2} + \eta_i + \eta_m)}{1 + \exp(\beta_{1 \text{ or } 2} + \eta_i + \eta_m)} \ \ \eta_i \sim N(0, \gamma_i^2), \eta_m \sim N(0, \gamma_m^2) \tag{10}$$

which allows for persistent station and market heterogeneity in a relatively flexible way. For particular random draws η_m and η_i and for a value of $\beta_{1 \text{ or } 2}$, $\sigma^*_{im(1 \text{ or } 2)}$ can be calculated for each station. Given values of β_2, α and $\sigma^*_{im(1 \text{ or } 2)}$ for all stations in a market, I solve for up to two stable and symmetric equilibria ($\sigma^*_{im(2|1 \text{ or } 2)}$) by iterating on the system of equations defined by (8).[20] The simulated log-likelihood objective function is calculated using the values of $\sigma^*_{im(1 \text{ or } 2)}$, the values of $\sigma^*_{im(2|1 \text{ or } 2)}$ for each equilibrium (A and B) and the choices of each observed station, averaged over 100 simulated

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[19]It is well known that SML is inconsistent unless the number of simulation draws is increased fast enough as the number of observations increases. I use at least 50 draws per market for a dataset including 144 markets. Some preliminary Monte Carlo experiments indicated that with at least 50 simulations the degree of bias is small.

[20]If $\alpha \geq 0$ then the two action game has at most two stable equilibria and all equilibria will be symmetric. If $\alpha < 0$ then there may be more equilibria, some of which may be asymmetric. Fortunately, the two-step results, which do not impose the number, stability or symmetry of equilibria, suggest that $\alpha \geq 0$ is the relevant case.

draws of η_m and η_i.

$$\ln L = \sum_{m=1}^{M} \ln \frac{1}{S} \sum_{s=1}^{S} \tag{11}$$

$$\left(\begin{array}{c} \lambda \prod_{i=1}^{N_m} \left[1 - \sigma^s_{im(1 \text{ or } 2)} \right]^{n_{im0}} \left[\sigma^s_{im(1 \text{ or } 2)} \left(1 - \sigma^{s*}_{imA(2|1 \text{ or } 2)} \right) \right]^{n_{im1}} \left[\sigma^s_{im(1 \text{ or } 2)} \sigma^{s*}_{imA(2|1 \text{ or } 2)} \right]^{n_{im2}} \\ + (1 - \lambda) \prod_{i=1}^{N_m} \left[1 - \sigma^s_{im(1 \text{ or } 2)} \right]^{n_{im0}} \left[\sigma^s_{im(1 \text{ or } 2)} \left(1 - \sigma^{s*}_{imB(2|1 \text{ or } 2)} \right) \right]^{n_{im1}} \left[\sigma^s_{im(1 \text{ or } 2)} \sigma^{s*}_{imB(2|1 \text{ or } 2)} \right]^{n_{im2}} \end{array} \right)$$

where n_{imt} is the number of days on which station i chooses action t, n_{im0} counts the number of times station i chooses neither action 1 nor action 2 and the dependence of the σs on the parameters and the simulation draws have been suppressed. If there is only one equilibrium for particular parameters and draws then $\sigma^{s*}_{imA(2|1 \text{ or } 2)} = \sigma^{s*}_{imB(2|1 \text{ or } 2)}$.

As already noted I lack timing, but not characteristics data, for some smaller stations which are not monitored by Mediabase. I allow for the existence of these stations, under the assumption that they have the same payoff parameters and distribution of unobserved heterogeneity as those which are observed, by taking draws of η_i and solving for equilibrium strategies for all stations including those which are not in the Mediabase sample.[21] The value of the simulated likelihood function (11) is calculated using only stations which are in the timing sample with the remaining stations affecting the equilibrium strategies of the sample stations.

Comparison of the Two Estimation Procedures

The two estimation procedures have different strengths. The two-step procedure is computationally simple which allows me to estimate specifications with many observable characteristics. However, the two-step estimates are only consistent with a long panel of timing choices for each station, whereas I have a maximum of 59 observations on any particular station-hour. The two-step procedure also ignores the existence of stations which are not observed, which is likely to bias the results in smaller markets where the Mediabase sample is particularly incomplete. The consistency of the NFXP procedure only requires that there is no systematic correlation between whether data are missing and

[21] I include all stations which have a market share above 1% in either the Spring or Fall quarters of 2001.

timing choices.

6   Empirical Results

I present the results from the two-step and NFXP approaches, before describing three tests of the maintained assumption that no station changes its strategy and no market changes which equilibrium it is in during my data. Several implications of the results are discussed in Section 7.

Separate specifications are estimated for each hour. Any strategic incentives are expected to be stronger during drivetime, because of the greater propensity of in-car listeners to switch stations. For similar reasons one might expect longer average commutes or a higher proportion of people commuting by car to increase strategic incentives. However some preliminary estimates provided no evidence for this once market size is controlled for (larger markets have longer average commutes). This result may also reflect the fact that long commutes may often take people outside their home radio markets so these commuters may be irrelevant to the timing decisions of home market stations. [22]

I also allow strategic incentives to vary with three observable market characteristics: market rank (higher for smaller markets), ownership concentration and listenership asymmetry. The intuition for why these variables may affect strategic incentives is fairly simple (Sweeting (2006) presents theoretical models examining these comparative statics). Smaller markets have fewer stations. If switching listeners try every station before listening to a commercial then a station will only be able to maintain its audience during a commercial if all stations play commercials at the same time. The probability that this happens increases when there are fewer stations, increasing the incentive of every station to try to coordinate.[23] A similar result holds if listeners only try a sample of stations but try more stations in larger markets. Asymmetries in station listenership can strengthen coordination incentives if switchers are much more likely to try one or two dominant stations. In this case, a station can keep most of its audience as long as it plays commercials at the same time as the dominant stations giving it more incentive to try to coordinate than in a market where stations are symmetric. Ownership

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[22]For example, radio markets within commuting distance of Boston, MA include Worcester, Springfield, Providence RI, Portsmouth NH, Manchester NH, New Bedford-Fall River and Cape Cod.

[23]I present results from specifications which include market rank rather than the number of stations. Results using the latter variable are qualitatively similar, but the coefficients vary more across specifications.

concentration should affect timing strategies because commonly owned stations should internalize audience externalities. If strategies are strategic complements ($\alpha > 0$) increased coordination between the commonly owned stations should lead to more coordination between stations owned by other firms as well.[24]

Two Step Estimates

[TABLE 5 HERE]

Table 5 presents the two step results. Columns (1)-(4) present estimates for each hour for specifications which allow for observable heterogeneity in non-strategic preferences ($\beta_{:55}$) but assume that strategic incentives (α) are identical across markets and symmetric across stations within a market. The estimated α is positive and significant at the 1% level for both drivetime hours, implying that stations do want to play commercials at the same time. Very few of the covariates affecting non-strategic preferences are statistically significant (Oldies at the 1% level for 4-5 pm and Clear Channel and ownership HHI at 5% and 10% levels for 5-6 pm). The coefficients are also small: for example, the Clear Channel coefficient for 5-6 pm implies that the conditional probability that a station has a commercial at :55 increases by 0.025 when the station is owned by Clear Channel compared with a mean probability of 0.50.[25] The lack of observable station-specific variables affecting timing preferences in significant ways implies that "exclusion restriction" approaches to identification are likely to be ineffective.

For non-drivetime hours (columns (3) and (4)) the strategic incentive coefficients are positive but statistically insignificant. The difference between the drivetime and non-drivetime results is consistent with greater listener switching during drivetime strengthening strategic incentives. There are also stronger format specific differences in non-strategic preferences outside drivetime.[26]

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[24]I allow common ownership to affect coordination by allowing it to affect the strength of strategic incentives rather than, for example, explicitly modelling joint decision making across multiple stations.

[25]The Clear Channel and Infinity coefficients may be small because the sample stations are too large to be programmed centrally. The larger 9-10 pm coefficients may reflect use of syndicated programming, with common times for commercials, during evening hours. No sample stations used syndicated programming during afternoon drivetime.

[26]Adult Contemporary, Oldies and Country stations have later commercials, probably because stations in these formats are more likely to have news headlines at the start of the hour. If listeners do not want to miss these headlines, then stations may want to play commercials immediately prior to them.

The specifications in columns (5)-(8) allow for persistent unobserved market and station heterogeneity in stations' non-strategic preferences and for stations to be more concerned about how they time their commercials relative to stations in their own format. The heterogeneity enters as two normally distributed random effects. The station random effects allow for an individual station to persistently make a particular timing choice while the market random effects allow a non-strategic explanation for why stations in the same market make the same timing choice. The within-format strategic effect is allowed for by including an additional term in the model which corresponds to the term in the inner brackets of (8) calculated only using stations in the same market-format.

The estimates show that persistent unobserved station heterogeneity in timing preferences is important in all hours but that there is no significant unobserved market heterogeneity in non-strategic preferences. The "all station" strategic incentives for drivetime hours remain significant. A legitimate concern is that this result partly reflects the restrictive parametric form assumed for the market heterogeneity. However, for the non-drivetime hours the difficulty of separately identifying strategic incentives and market-heterogeneity results in much larger standard errors on many of the variables including the all station strategic incentive, despite the same functional form assumption being made.

The within-format strategic incentive is small and statistically insignificant in both drivetime hours implying that, at least when it comes to timing decisions, music stations interact in a fairly symmetric way. This finding is plausible if listeners switch primarily between preset stations and tend to preset one station in each format.[27] The within-format strategic incentive for 9-10 pm is significant but it only offsets the negative and insignificant all station coefficient.

Columns (9) and (10) allow the all station strategic incentive to vary with observable market characteristics (market rank, ownership concentration and listenership asymmetry) during drivetime. The positive market rank coefficients are consistent with there being more coordination in smaller markets but they are only weakly significant. These coefficients are likely to be downward biased because the incomplete sample in these markets will lead to stations expectations' about how many other stations will play commercials being poorly measured. None of the ownership or listenership

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[27]Stations share listeners as much across formats as within formats. For example, in Fall 2002 there were 6 Rock and 9 non-Rock home contemporary music stations in Boston. Arbitron (2003) reports that on average 15.6% (15.3%) of the listeners to a Rock station listened to each of the other Rock (non-Rock) stations.

asymmetry interaction coefficients are significant.

I have also estimated several specifications whose results are not reported. One of these allows for a non-linear strategic incentive by including the square of the variable which multiples the α coefficient in (8). Nonlinearities might arise if a station has an incentive to play its commercials at a different time, to attract a large number of switchers, once the vast majority of other stations are coordinating. The coefficients on the squared term in specification like columns (1)-(4) are all statistically insignificant (e.g. 0.417 (1.234) for 4-5 pm and -0.586 (0.844) for 5-6 pm) with the other coefficients almost unchanged. This result could be explained by linearity being the correct model or by the variation in other stations' strategies being too limited to identify more complicated effects.

NFXP Estimates

The simplest NFXP specification, whose results are reported in columns (1)-(4) of Table 6, assumes that there is no unobserved heterogeneity in either $\beta_{:55}$ or α. I allow at most one observable station-specific variable to affect non-strategic preferences. Based on the two-step results, this variable is an Oldies dummy for 4-5 pm and a dummy for CHR, Rock and Urban stations outside drivetime.[28]

[TABLE 6 HERE]

The estimates of α are positive and significant for both of the drivetime hours, implying that stations want to play commercials at the same time, and, consistent with mismeasurement affecting the two-step estimates, the coefficients are larger than in columns (1) and (2) of Table 5. α is also estimated to be positive and significant outside drivetime although the incentive to coordinate is too small to support multiple equilibria (so the λ parameters are not identified).

Columns (5)-(8) show specifications with both observable and unobservable heterogeneity in the strength of strategic incentives ($\alpha_m = X_m \alpha + \eta_\alpha$ where $\eta_\alpha \sim N(0, \gamma_\alpha^2)$). As well as the market rank group dummies I include a linear market rank variable but its coefficient is always small and insignificant. Coordination incentives are clearly stronger in smaller markets during drivetime and

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[28] A few stations change formats during 2001. When estimating the model I treat stations as being in their Spring 2001 formats throughout the year.

the coefficients are similar across the drivetime hours. The listenership asymmetry coefficients are also positive and significant during drivetime, which is what one would expect if stations want to coordinate, but the coefficients are quite small. There is estimated to be significant unobserved heterogeneity (γ_α^2) in strategic incentives across markets in all hours, but during drivetime differences in market size explain quite a lot of the total variation.

Columns (9) and (10) allow for persistent unobserved station heterogeneity in non-strategic preferences ($\beta_{:55i} = X_i\beta_{:55} + \eta_{\beta_{:55}}$ where $\eta_{\beta_{:55}} \sim N(0, \gamma_{\beta_{:55}}^2)$). This heterogeneity, which could be associated with a station reserving particular times for non-commercial programming (e.g., "weather on the ones") is assumed to be normally distributed and to be observed by all stations when they choose their timing strategies. Consistent with the two-step results, this type of heterogeneity is clearly significant, but allowing for it only has a relatively small effect on the estimated strategic incentives. An exception is the listenership asymmetry coefficient for 5-6 pm which becomes negative: therefore the Model 2 results for this variable should be treated with caution. A disappointing feature of the results is that ownership concentration is not significant in any of the specifications.

Testing for Changes in Station Strategies/Within Market Multiple Equilibria

Before discussing the implications of the results, I test the validity of the assumption that each station uses the same strategy (and each market remains in the same equilibrium) throughout the data, although these strategies may differ across stations. I use three tests which exploit different features of the data, and they could be applied to look for evidence of multiple equilibria in other settings. One of tests (the pairwise correlation test) also provides evidence in favor of the incomplete information assumption.

Modified Likelihood Ratio Test (MLRT)

MLRTs are used in the statistics literature (Chen et al. (2001b) and Chen et al. (2004)) to test for the appropriate number of components in binomial mixture models. As multiple equilibria generate a likelihood which is the same as a binomial or multinomial mixture, I apply the Chen et al. (2001) test market-by-market to examine whether there is evidence of multiple equilibria being played within

markets. The test assumes that there is no persistent observed or unobserved heterogeneity across stations. If a single equilibrium is played every day (the null hypothesis) then the probability that n_{2m} stations are observed choosing action 2 on any given day is $\binom{N_m}{n_{2m}}(\sigma_{2m}^*)^{n_{2m}}(1 - \sigma_{2m}^*)^{N_m - n_{2m}}$. If two equilibria are played on different days then the probability is (5) with $E = 2$, a binomial mixture model with two components. Under this alternative hypothesis the model is estimated using the modified log-likelihood

$$l^M(\lambda_m, \sigma_{A2m}^*, \sigma_{B2m}^*) = l(\lambda_m, \sigma_{A2m}^*, \sigma_{B2m}^*) + C\log(4\lambda_m(1 - \lambda_m)) \tag{12}$$

where $l(\lambda_m, \sigma_{A2m}^*, \sigma_{B2m}^*)$ is the standard log-likelihood for a two component mixture model and the second term, where C is a positive constant, solves the problem that some of the parameters are not identified under the null when only the standard log-likelihood is used. The test statistic is $M = l^M(\widehat{\lambda_m}, \widehat{\sigma_{A2m}^*}, \widehat{\sigma_{B2m}^*}) - l^M(\frac{1}{2}, \widehat{\sigma_{2m}^*}, \widehat{\sigma_{2m}^*}))$ where $\widehat{\sigma_{2m}^*}$ is the choice probability for a single component mixture, and its asymptotic distribution is an equal mixture of χ_0^2 and χ_1^2 distributions. Chen et al. (2001) show that this test is the asymptotically most powerful under local alternatives.[29]

[TABLE 7 HERE]

I apply the test defining the binomial actions in three different ways. The first way defines one action as having a commercial at either :50 or :55 with the other action being having a commercial at neither of these times. The second way defines one action as having a commercial at :55 with the other action not having a commercial at :55. The third way, which comes closest to focusing on the conditional game between stations choosing :50 or :55, defines one action as having a commercial at :55 with the other action having a commercial at :50 (with stations choosing neither of these times ignored). The results are reported in panel (a) of Table 7, which shows the proportion of the markets where the null of a single component is rejected at the 5% level.[30] The proportion of markets where the null is rejected is small (less than 6%) in all station hours, consistent with a single equilibrium

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[29] Chen et al. (2004) present a test where a two component model can be tested against a model with $k > 2$ components. This test is potentially useful for testing how many equilibria need to be allowed for.

[30] The test only uses the 124 markets with at least three observed stations because, as discussed in Section 4, a two component model is not identified with fewer than three stations.

being played within each market.[31]

Pairwise Station Correlation Test

The MLRT test is attractive in the sense that it uses the choices of all stations within a market simultaneously, but it makes the assumption, which can be rejected once we allow for persistent unobservable station heterogeneity in $\beta_{.55}$, that stations within a market are identical. The remaining tests do not make this assumption, and instead look at variation within a station's timing choices, or a pair of stations' timing choices, over time.

The pairwise correlation test examines whether there is any time-series correlation in the timing choices of pairs of stations in the same market. If a market switches from one equilibrium to another then stations' strategies should change at the same time causing time-series correlation in their actions. On the other hand, if each station uses the same strategy every day (the null hypothesis) then actions will only vary from day-to-day due to the private information and iid ε payoff shocks so there should be no correlation.

There could also be significant correlations if the εs are not private information. If they are private information then each station's strategy will be a mapping from its *own* εs to its timing choice. If they are observed by other stations (complete information) then a station's strategy will be a mapping from *all stations' εs* to its timing choice so that, even if the εs are iid and stations' strategies do not change, there should be correlations in stations' choices.

I implement the test using the alternative choice definitions used for the MLRT test. For each pair of stations in the same market I calculate the correlation coefficient for these binary actions.[32] The results are reported in panel (b) of Table 7. There are only significant correlations for a small proportion of pairs (and in these cases there is a roughly equal mix of positive and negative correlations) consistent with incomplete information and with stations using the same strategies over time.

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[31] One can also perform a joint test by adding the test statistics from each market and simulating this new statistic's asymptotic distribution. The null that there is only one equilibrium in each market cannot be rejected for any hour. The same conclusion holds for the joint version of the other tests.

[32] The significance of the estimated correlation coefficient $\widehat{\rho}$ is assessed using a t-distribution with $(n-2)$ degrees of freedom where n is the number of days when both stations in the pair are observed in the data.

Runs Test[33]

The final test is a "runs test" which looks for serial correlation in a station's own choices. A change in a station's strategy during the year should affect how frequently it makes a particular timing choice on consecutive days. The test is implemented by defining binary choices as before, ordering the data for each station by the calendar date and calculating how many runs there are of a particular choice and whether there are more or less runs than one would expect if the data was randomly ordered.[34] The results are reported in panel (c) of Table 7. Once again, the test statistic is only significant for a small proportion of stations in each case.

7   Discussion

The parameter estimates provide consistent support for the hypothesis that stations want to play commercials at the same time during drivetime, especially in smaller markets. I now examine how strong the estimated incentives actually are, why equilibrium coordination may be limited, and the role that multiple equilibria play in identifying the parameters.

Strength of Strategic Incentives and Equilibrium Coordination

[TABLE 8 HERE]

The strength of strategic incentives and the degree of equilibrium coordination implied by the estimated values of α can be illustrated using a simplified example. Suppose that stations are identical, :55 is slightly more attractive for commercials ($\beta_{:55} = 0.001$) and that all stations have commercials at either :50 or :55 with probability 0.6 (close to the drivetime average). For different values of α, Table 8 shows the change in a station's best response probability when the conditional probability that other stations choose :55 increases from 0 to 1 (the unconditional probability changes

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[33]I would like to thank one of my referees for suggesting this test.

[34]For a (0,1) action, a run is defined as a sequence of identical choices (e.g., 000 or 11). If n_{0s} is the number of 0s chosen then the expected number of runs is $\frac{2n_{0s}n_{1s}}{n_{0s}+n_{1s}} + 1$. The test statistic $z_s = \frac{r_s - \left(\frac{2n_{0s}n_{1s}}{n_{0s}+n_{1s}}+1\right)}{\sqrt{\frac{2n_{0s}n_{1s}(2n_{0s}n_{1s}-(n_{0s}+n_{1s}))}{(n_{0s}+n_{1s})^2(n_{0s}+n_{1s}-1)}}}$, where r_s is the number of observed runs, should have an approximate standard normal distribution.

from 0 to 0.6) and the *Nash equilibrium* probabilities with which stations choose each action. An entry of "(0.6259,0.3741)" in the third column means that there is a stable equilibrium where stations choose :55 with conditional probability 0.6259 (unconditional probability $0.6 * 0.6259 = 0.376$) and :50 with conditional probability 0.3741 (unconditional probability 0.224). For values of α above 3.35 there is an additional stable equilibrium in which stations are more likely to choose :50 than :55.

The NFXP Model 3 results for 4-5 pm imply that the mean values of α for large markets (ranked 1-49), medium markets (50-99) and small markets (above 100) are 0.04, 1.34 and 2.9 respectively. The unobserved heterogeneity in α across markets implies that almost 38% of markets have αs greater than 2 and 30% of small markets have αs greater than 4. For 5-6 pm the mean values of α are larger for each size group, but there is less heterogeneity, so around 20% of small markets have αs above 4. Looking at the effect of other stations' strategies on a station's best response incentive (the second column of Table 8), the estimated coordination incentives are clearly quite strong in medium and small markets, in the sense that a station would change its timing strategy significantly if all other stations changed the time at which they were playing commercials. However, only in markets where α is greater than 3.35 (primarily small markets) is the estimated strategic incentive strong enough to result in significantly more equilibrium coordination (i.e., overlap of commercials) than there would be if $\alpha = 0$. So the results show that while stations may want to coordinate, equilibrium coordination is very limited in the majority of markets and especially in larger markets.

Given how many people avoid commercials by switching stations, there are two possible explanations for why equilibrium coordination is limited in most markets. The first explanation, which follows from the discussion in the Introduction, is that an advertiser may not be able to perfectly align a station's timing incentives with its own because data on the audience of commercials is not collected. Limited coordination may therefore arise from a vertical (principal-agent) incentive problem. The second explanation is that externalities in the timing game, interacting with the private information payoff shocks, lead to limited coordination. This could happen even if there is no principal-agent problem. Instead limited coordination would arise from a horizontal coordination failure between stations (or between advertisers).

A formal quantification of how vertical incentive problems affect timing requires more data than is available: for example, one would need to know in a detailed way how timing choices affect the audience of commercials and how this affects the sales of advertisers, taking into account that people who tend to switch stations may be either more or less likely to buy an advertised product. However, using the estimated model I can identify whether externalities are potentially important by comparing stations' Nash equilibrium strategies with their (counterfactual) strategies if the externalities between stations were internalized. These joint-payoff maximizing strategies, calculated using formulae from Brock and Durlauf (2001), assume that the εs remain private information so that a station's choice can only be based on the value of its εs, but that each station tries to maximize the expected payoffs of all stations. These strategies are reported for different values of α in the fourth column of Table 8. If α is above 2 joint-payoff maximizing strategies involve a high degree of coordination, even if Nash equilibrium strategies lead to little coordination. For example, if $\alpha = 2.5$ the probability that two stations with commercials :50 or :55 play them at the same time is 0.86 under joint payoff-maximizing strategies and 0.50 under Nash equilibrium strategies.[35] As mentioned above, around 40% of all markets (and over 50% of medium and smaller markets) are estimated to have αs above 2, so the parameter estimates are consistent with horizontal coordination failures being a major cause of weak equilibrium coordination in these markets. The fact that we observe less coordination in larger markets is also consistent with this view if the externalities become larger when the number of stations increases.

The Role of Multiple Equilibria in Identification

[TABLE 9 HERE]

Section 4 showed how multiple equilibria can play a role in identifying payoff parameters. This prompts two questions about the actual results: in how many markets can multiple equilibria be supported? and what is the role of multiple equilibria in identifying the parameters in my setting? Table 9 shows the proportion of (simulated) markets in which multiple equilibria are supported for the

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[35]When α is below 2 coordination remains limited because joint payoffs are maximized by stations trying to maximize the value of their own εs, rather than trying to coordinate with other stations.

three different models estimated using the NFXP algorithm for 4-5 pm. The estimated values of λ imply that in the markets where multiple equilibria are supported there are roughly equal proportions of markets coordinating on :50 and :55. For Model 1 variation in whether multiple equilibria are supported only comes from variation in the proportion of the stations having commercials at :50 or :55 across markets (when this proportion is high enough multiple equilibria can be supported). Models 2 and 3 allow for observed and unobserved heterogeneity in α across markets: for 4-5 pm multiple equilibria are supported in many of the simulated smaller markets, but they are only supported in large markets with very high η_α draws. The number of markets with multiple equilibria falls in Model 3 because of the persistent station-specific heterogeneity in non-strategic preferences. If a few stations have a strong preference for playing commercials at :55 then, unless α is exceptionally high, an equilibrium where other stations play commercials at :50 cannot be supported. On the other hand, if some stations have strong preferences then stations with weak preferences will choose to coordinate with them, so allowing for this form of heterogeneity does not necessarily lead to less equilibrium coordination. The numbers are similar for 5-6 pm whereas outside drivetime the average values of α are so small that multiple equilibria can only be supported in a small proportion of markets (less than 3% for Model 2). In simulated markets where there are multiple equilibria the degree of coordination varies, reflecting the heterogeneity of α_m in NFXP Models 2 and 3, but for Model 3 the average degree of coordination in this subset of markets is quite high with the average conditional probability that :55 is chosen close to 0.8 in one equilibrium and 0.2 in the other.

Identification of an incentive to coordinate (a positive α) separately from non-strategic incentives comes from variation in the degree and timing of clustering across markets, in a way which cannot be rationalized by the factors which are allowed to affect non-strategic preferences. In the most complete model (NFXP Model 3) variation can arise from three sources. First, multiple equilibria can lead to coordination on *different times in different markets* for the same set of observed variables. Second, if α is positive then there will be more clustering of commercials at a particular time (:50 or :55) in markets where the proportion of stations having ads at the end of the hour (i.e., $\sigma^*_{1 \text{ or } 2}$) is higher. Of course, this type of variation may result from multiple equilibria in the full game with

more timing choices. Third, if α is positive then a station will be more likely to choose the same time for commercials as other stations when *the degree of clustering among these other stations is higher* (even if this clustering always happens on the same time). Variation in the degree of clustering of other stations in Model 3 can arise from unobserved station-specific heterogeneity in $\beta_{:55}$ and the unobserved market heterogeneity in α.

[TABLE 10 HERE]

To assess the importance of each type of variation I simulate 50 datasets from each of five variants of NFXP Model 3 for 5-6 pm. Each variant allows for a different combination of these sources of variation. For each simulated dataset I estimate the two-step model corresponding to column (2) of Table 5 (allowing the observable covariates which affect α in NFXP Model 3 to affect $\beta_{:55}$ in a flexible way), and compare the average value of the estimated strategic incentive from each of the variants.[36] The results are shown in Table 10. The idea is that if the incentive to coordinate is identified then the estimated values of α should be consistently positive, as the true data generating process has an average positive value of α.

When I shut-off all three sources of variation (which means setting all of the unobservable heterogeneity parameters to zero and the equilibrium selection parameter (λ) to 1) the average estimated value of α is close to zero with a relatively large standard deviation, consistent with α not being well identified by the data. When I allow for multiple equilibria, but exclude the other sources of variation, the estimated mean α is positive and significantly different from zero. Therefore multiple equilibria provide *sufficient* variation to identify that stations want to coordinate, even though there are only multiple equilibria in the smallest markets. However, multiple equilibria are not *necessary* because the other sources of variation are also sufficient, although including only variation in the proportion of stations playing ads at :50 or :55 results in smaller and more volatile estimates of α.

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[36]I estimate a two-step model to reduce the computational burden because re-estimating the NFXP model would require re-starting a computationally expensive estimation procedure from multiple starting points for each simulated dataset in order to be confident that the estimates with the highest log-likelihood have been found.

8 Conclusion

The article was motivated by the observation that stations may or may not want to coordinate on the timing of commercials, because advertisers can only monitor the effectiveness of their advertising in an imperfect way. I find that stations do prefer to play their commercials at the same time, which suggests that the incentives of stations are at least partially aligned with those of advertisers, although equilibrium coordination is far from perfect.

An interesting direction for future research in this industry is to look more closely at why equilibrium coordination is imperfect. As explained above, externalities in the timing game combined with the difficulties that stations have in playing commercials at predictable times, because they have to be placed around other types of programming, are likely to provide part of the explanation. This issue is particularly relevant for radio because radio stations, unlike television stations, make little use of pre-recorded or scripted programming. The difficulty of assessing how effective commercials on different stations actually are, which may lead to station and advertiser incentives being misaligned, remains an important issue in the industry. For example, Google's CEO cited this difficulty as the main reason why Google abandoned its attempt to develop a platform for selling radio advertising time.[37] From this perspective, it will be interesting to see how Nielsen Media Research's decision to release information on the viewership of television commercials separately from non-commercial programming audiences will affect both timing strategies and the ways in which television commercials are sold.

The article has also made a methodological contribution by investigating how the existence of multiple equilibria in the data can aid the identification of strategic incentives. This approach contrasts with the commonly-made, but strong, assumption that only a single equilibrium is observed. If the mixture of equilibrium strategies in the data is identified then having multiple equilibria will always be helpful for identification because each equilibrium provides additional equations which the parameters have to satisfy. However, allowing for multiple equilibria can significantly increase computational costs (particularly if it is necessary to find all of the equilibria repeatedly during

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[37] Google Chief Executive Eric Schmidt quoted in the "Radio Tunes Out Google in Rare Miss for Web Titan", Wall Street Journal, May 12, 2009, p. 14.

estimation) and relying on multiple equilibria for identification may make the results even more dependent on the correct specification of the model. For these reasons I see particular value in future research, perhaps building off the ideas in Section 6, aimed at developing tests for the possible presence of multiple equilibria without requiring the full model to be estimated.

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Appendix

This Appendix describes the NFXP estimation algorithm. Following the text, I describe the procedure for Model 1 and then explain how additional heterogeneity is added for Models 2 and 3.

Estimation proceeds in the following steps:

1. S ($S = 100$ for Model 1) sets of Halton draws for e_i and e_m are drawn from a standard normal distribution for each station and market. Draws are made and the game is solved for all music stations whether or not they are in the airplay sample.[38] e_i and e_m are held constant during estimation while $\eta_i^s = \gamma_i e_i^s$ and $\eta_m^s = \gamma_m e_m^s$ vary with the parameters γ_i and γ_m;

2. for each market for a given set of the parameters and draws,

   (a) (10) is used to calculate $\sigma_{im(1 \text{ or } 2)}^*$;

   (b) the equilibrium choice probabilities $\sigma_{im(2|1 \text{ or } 2)}^*$ are solved for by iterating equations (8) for each station in the market. Experimentation showed that to reliably find multiple equilibria, it is necessary to begin the iteration process from extreme points in the probability space (e.g., every station chooses action 1 with probability 0.99 or 0.01) and to update strategies rather slowly.[39] I take strategies to have converged when the choice probabilities change by less than $1e - 8$. This approach can only find stable and symmetric equilibria and, for given values of the $\sigma_{im(1 \text{ or } 2)}^*$s, the conditional game can have at most two stable and symmetric equilibria if $\alpha > 0$;

3. the choice probabilities are used to calculate the simulated log-likelihood based on the station-days which are observed in the sample

$$\ln L = \sum_{m=1}^{M} \ln \frac{1}{S} \sum_{s=1}^{S} \tag{13}$$

$$\left(\begin{array}{c} \lambda \prod_{i=1}^{N_m} \left[1 - \sigma_{im(1 \text{ or } 2)}^s \right]^{n_{im0}} \left[\sigma_{im(1 \text{ or } 2)}^s \left(1 - \sigma_{imA(2|1 \text{ or } 2)}^{s*} \right) \right]^{n_{im1}} \left[\sigma_{im(1 \text{ or } 2)}^s \sigma_{imA(2|1 \text{ or } 2)}^{s*} \right]^{n_{im2}} \\ + (1 - \lambda) \prod_{i=1}^{N_m} \left[1 - \sigma_{im(1 \text{ or } 2)}^s \right]^{n_{im0}} \left[\sigma_{im(1 \text{ or } 2)}^s \left(1 - \sigma_{imB(2|1 \text{ or } 2)}^{s*} \right) \right]^{n_{im1}} \left[\sigma_{im(1 \text{ or } 2)}^s \sigma_{imB(2|1 \text{ or } 2)}^{s*} \right]^{n_{im2}} \end{array} \right)$$

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[38] I include all commercial music stations with at least 1% shares of radio listening at some point during 2001.

[39] For example, in some models I update choice probabilities by the maximum of 0.001 or 2.5% of the difference between the current strategy and the best response. Updating more quickly can cause one of the equilibria to be missed.

where n_{imt} is the number of days on which station i chooses action t and action 0 is choosing neither action 1 nor action 2. $\sigma^{s*}_{imA(2|1 \text{ or } 2)}$ is the conditional equilibrium choice probability of choosing action 2 in equilibrium A given simulation draws s, observed station market characteristics and the structural parameters; and,

4. the parameters are updated using the Nelder-Mead algorithm and steps 2 and 3 are iterated until the parameters converge. Standard errors are calculated using the outer product of the gradients method with numerical derivatives.

Models 2 and 3 allow for observed and permanent unobserved market heterogeneity in α (Model 2) and permanent unobserved station heterogeneity in β_2 (Model 3). This requires additional simulated draws to be made in step 1, with these draws entering the equations (8). Introducing these draws increases the computational burden significantly so I use $S = 50$ rather than 100.

Table 1: Coverage of the Airplay Sample

	Largest 70 Sample Markets New York City, NY - Knoxville, TN	Smallest 74 Sample Markets Albuquerque, NM - Muskegon, MI
Average number of music stations in market	13.3	9.4
Average number of sample stations in market	10.3	4.9
Average % of music listening accounted for by sample stations	86.6	66.5

Note: statistics based on licensed commercial stations in contemporary music formats with enough listeners to be rated by Arbitron throughout 2001

Figure 1: Timing Patterns for Commercials Across 144 Markets

(a) 12 - 1 pm

(b) 5 - 6 pm
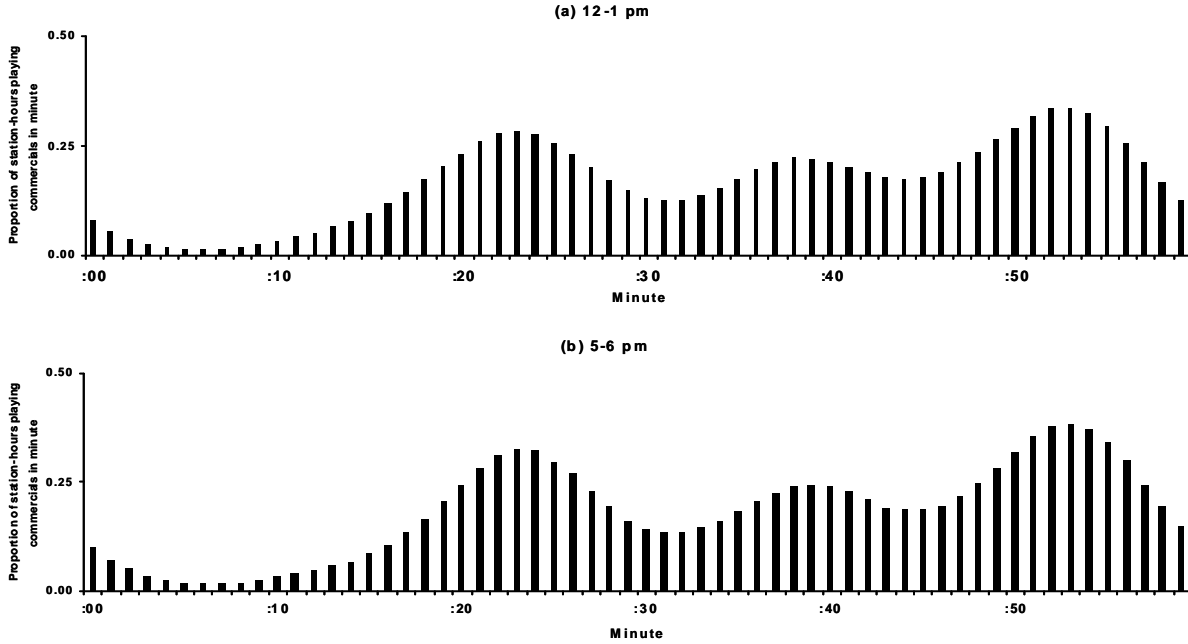
Table 2: Extract from a Sample Airplay Log

Time	Artist	Title	Release Year
5:02 PM	LIFEHOUSE	Hanging By A Moment	2000
5:06 PM	3 DOORS DOWN	Kryptonite	2000
5:08 PM	MORISSETTE, ALANIS	You Oughta Know	1995
5:12 PM	POLICE	Roxanne	1979
5:18 PM	PINK	Get the Party Started	2001
5:22 PM	BARENAKED LADIES	The Old Apartment	1996
5:24 PM	SUGAR RAY	Little Saint Nick	1997
5:26 PM	KEYS, ALICIA	Fallin'	2001
5:30 PM	KRAVITZ, LENNY	Dig In	2001
Stop Set	*BREAK*	*Commercials and/or Recorded Promotions*	-
5:40 PM	SHAGGY	Angel	2000
5:44 PM	TRAIN	Something More	2001
Stop Set	*BREAK*	*Commercials and/or Recorded Promotions*	-
5:54 PM	GOO GOO DOLLS	Black Balloon	1999
5:58 PM	CREED	With Arms Wide Open	2000

Figure 2: Timing of Commercials in Orlando, FL and Rochester, NY on October 30, 2001 5-6 pm

(a) Orlando, FL

(b) Rochester, NY
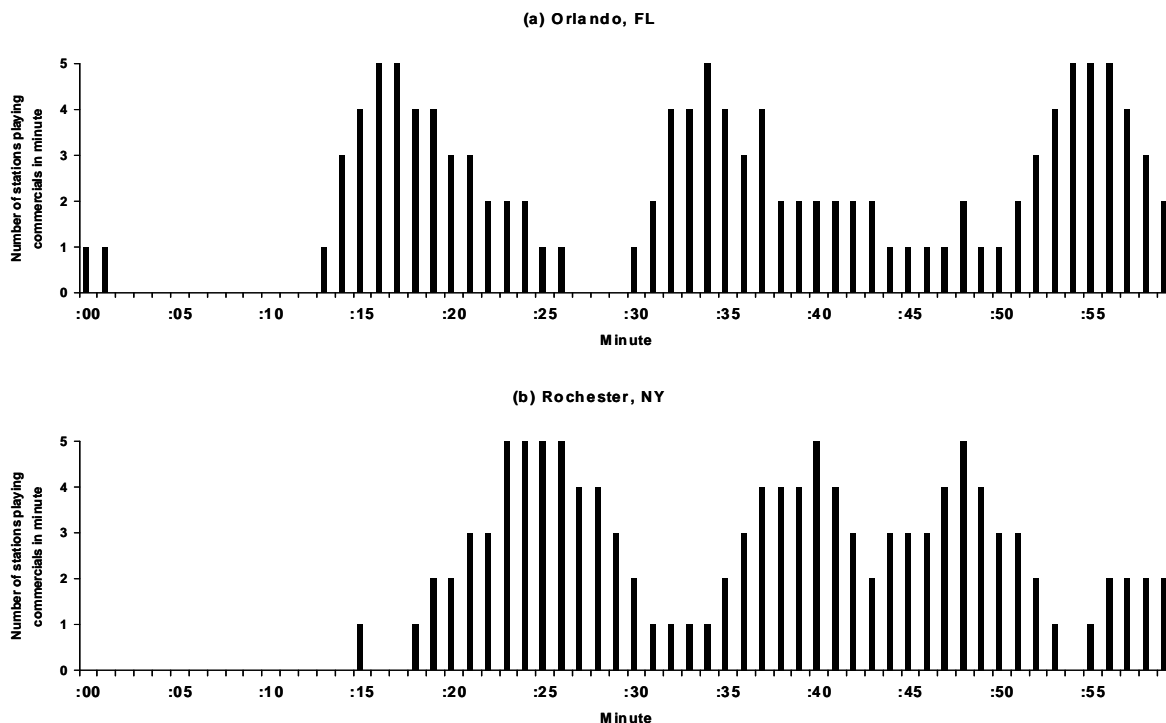
Table 3: Summary Statistics on Station Timing Choices

| Hour | total | Number of station-hours with | | | |
		no commercial at :50 or :55	commercial airing at :50, not :55	commercial airing at :55, not :50	commercial airing at both :50 and :55
12-1 pm	50,567	23,611	13,858	12,896	202
4-5 pm	50,520	22,118	13,878	14,231	293
5-6 pm	50,361	22,300	13,886	13,917	258
9-10 pm	49,828	23,756	12,812	13,079	184

Table 4: Timing Choices by Format for 12-1 pm and 5-6 pm

| 12-1 pm | Format | | | | | |
	Adult Contemporary	CHR/Top 40	Country	Oldies	Rock	Urban
No commercial at 12:50 or 12 :55	5,342	4,215	3,945	584	6,880	2,645
Commercial airing at 12:50	2,838	2,768	2,071	267	4,312	1,602
Commercial airing at 12:55	3,334	2,011	2,447	341	3,330	1,433
4-5 pm						
No commercial at 4:50 or 4 :55	5,158	3,994	3,724	523	6,361	2,540
Commercial airing at 4:50	3,155	2,488	2,439	334	3,876	1,594
Commercial airing at 4:55	3,191	2,516	2,376	330	3,928	1,576

Figure 3: Reaction Functions and Multiple Equilibria

(a) $\alpha=1$

(b) $\alpha=2.4$

(c) $\alpha=-1$

(d) $\alpha=-2.4$

15
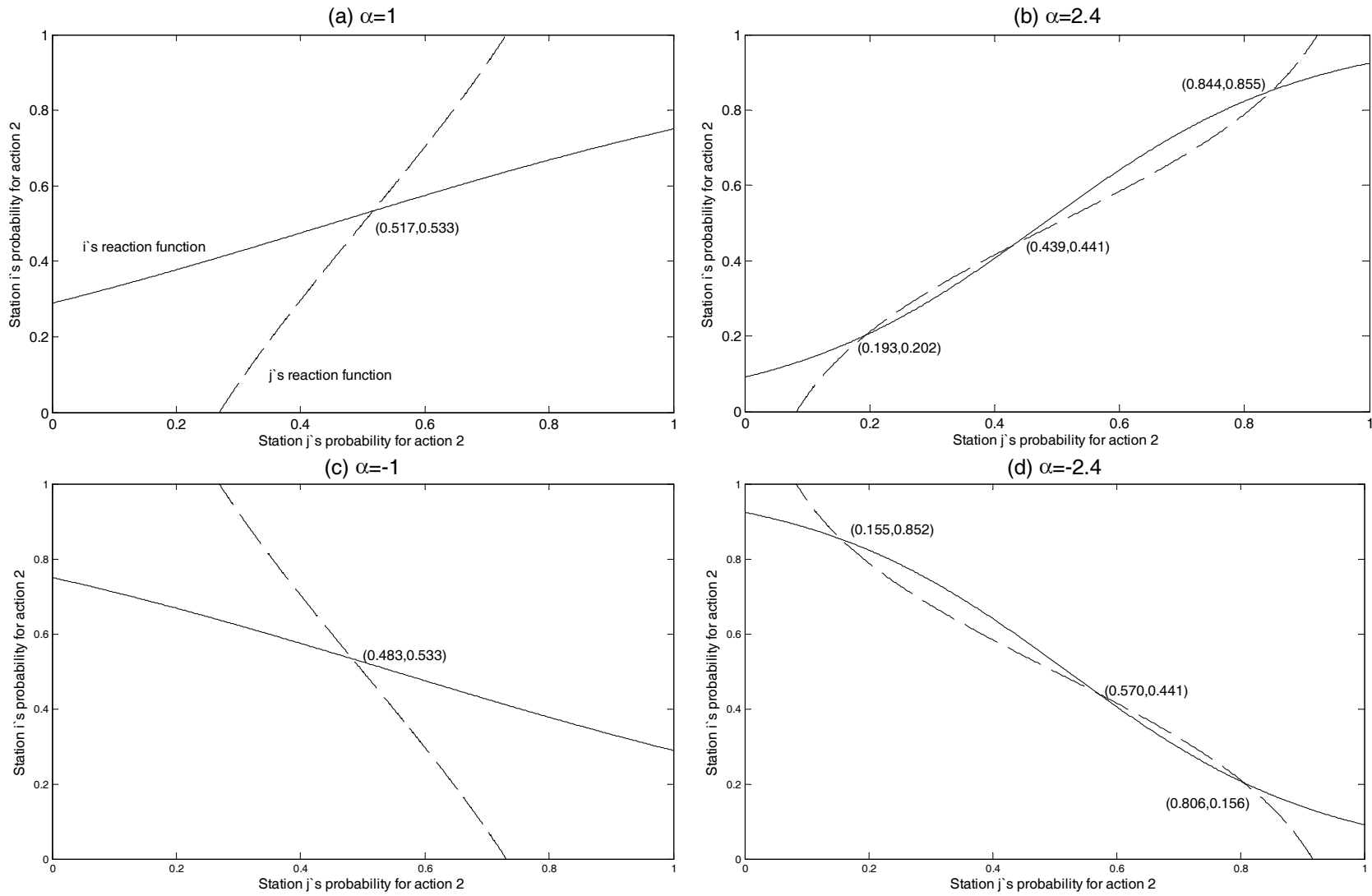
Figure 4: Identification: Theory and Evidence

(a) Comparison of PDF for Number of Stations Choosing :55 for a Model with One or Two Equilibria

■ Single Equilibrium, :55 Chosen with probability 0.5 □ Equal Mixture of Two Symmetric Equilibria, :55 Chosen with probabilities 0.6 and 0.4
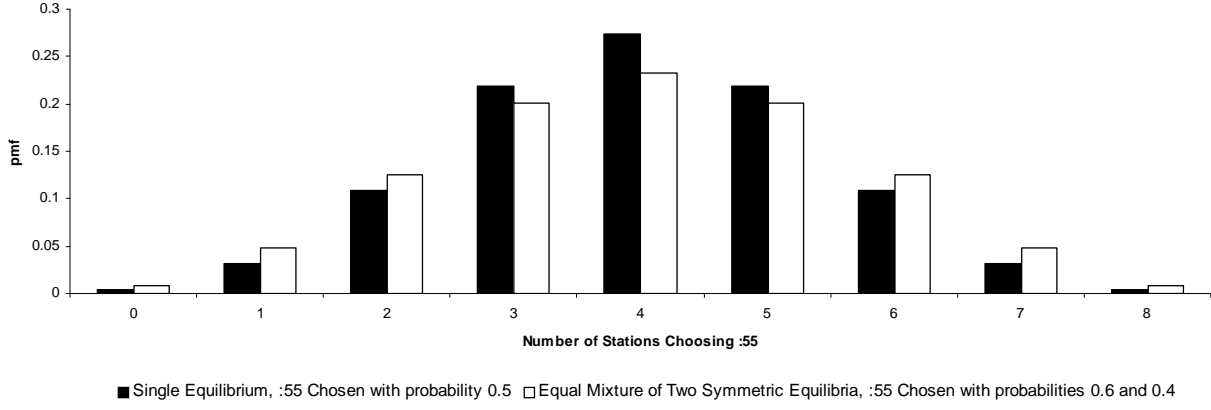
(b) Proportion of Stations Playing Commercials at :55 Conditional on Playing them at :50 or :55, All Markets
Heavy Line = Kernel Density for Actual Data, Thin Lines = Expected Kernel Density for a Binomial Model with 95% CIs

(i) 12-1pm

(ii) 5-6 pm
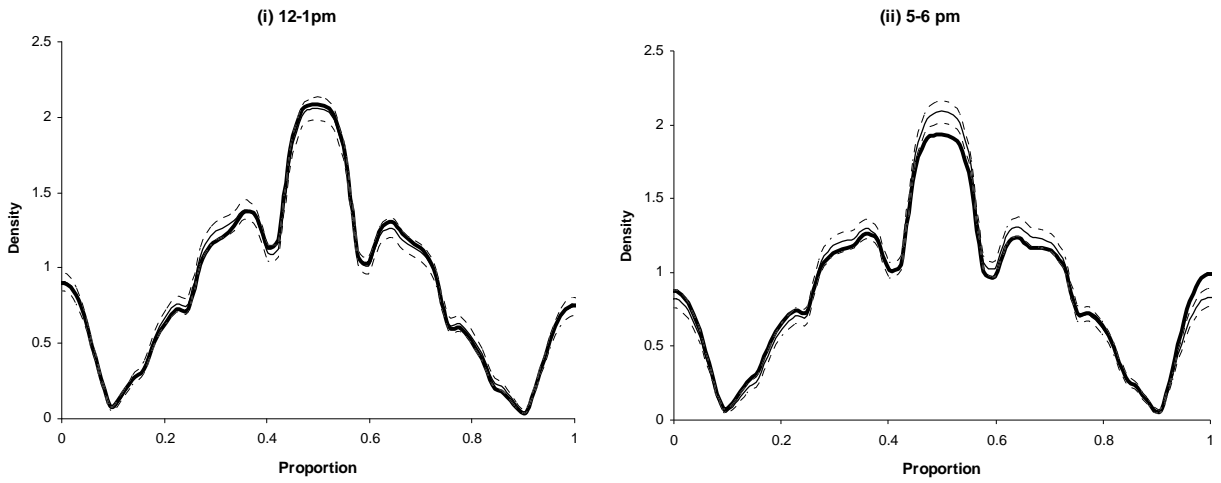
(c) Proportion of Stations Playing Commercials at :55 Conditional on Playing them at :50 or :55 in 74 Smallest Markets (Albuquerque, NM and smaller)

(i) 12-1 pm

(ii) 5-6 pm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Hour	4-5 pm	5-6 pm	12-1 pm	9-10 pm	4-5 pm	5-6 pm	12-1 pm	9-10 pm	4-5 pm	5-6 pm

$\beta_{:55}$ coefficients

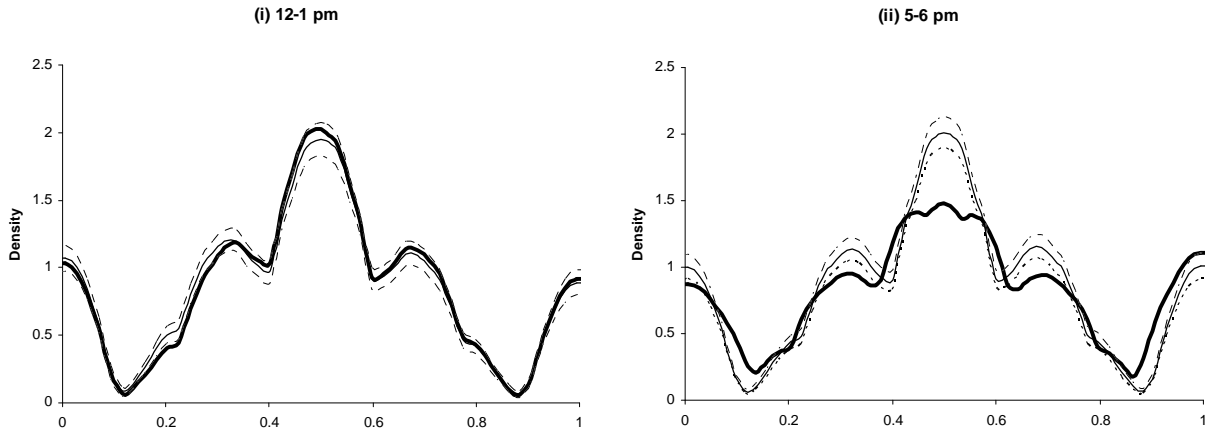|	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	1.921	-0.065	2.278	0.099	2.794***	0.217	2.723	0.340	3.097	0.129
	(1.426)	(1.234)	(1.833)	(2.564)	(1.038)	(0.924)	(10.595)	(18.850)	(1.785)	(1.552)
CHR	0.121	0.007	-0.482***	-0.850***	0.128	0.003	-0.633***	-0.915***	0.125	0.004
	(0.082)	(0.920)	(0.092)	(0.097)	(0.082)	(0.046)	(0.196)	(0.165)	(0.077)	(0.076)
Country	0.139	0.032	-0.026	0.322***	0.130*	0.008	-0.063	0.507***	0.118	0.008
	(0.088)	(0.101)	(0.067)	(0.102)	(0.074)	(0.084)	(0.072)	(0.132)	(0.058)	(0.082)
Oldies	0.413***	-0.046	0.159	0.395**	0.592***	-0.022	0.128	0.371**	0.552***	-0.037
	(0.137)	(0.141)	(0.130)	(0.212)	(0.156)	(0.114)	(0.122)	(0.166)	(0.093)	(0.132)
Rock	-0.023	-0.013	-0.418***	-0.679***	-0.055	-0.015	-0.532***	-0.745***	-0.065	-0.006
	(0.071)	(0.077)	(0.072)	(0.092)	(0.065)	(0.052)	(0.149)	(0.172)	(0.093)	(0.063)
Urban	0.101	-0.076	-0.278***	-0.704***	0.087	-0.122	-0.355***	-0.719***	0.066	-0.110
	(0.088)	(0.087)	(0.071)	(0.118)	(0.089)	(0.083)	(0.107)	(0.155)	(0.090)	(0.092)
Station's Share of	-0.482	0.025	0.527	0.263	-0.874	0.142	0.397	0.615	-0.830	0.211
Radio Listenership	(0.519)	(0.482)	(0.414)	(0.732)	(0.318)	(0.327)	(0.506)	(0.730)	(0.055)	(0.427)
Market Rank (/100)	0.078	0.052	-0.014	0.066	0.045	0.059	0.024	0.005	0.035	0.024
	(0.102)	(0.091)	(0.088)	(0.133)	(0.112)	(0.108)	(0.515)	(1.002)	(0.109)	(0.083)
Average Commuting Time	-0.004	0.006	-0.021	0.016	-0.005	0.006	-0.024	0.015	-0.008	0.004
	(0.007)	(0.006)	(0.011)	(0.012)	(0.006)	(0.004)	(0.062)	(0.123)	(0.010)	(0.007)
Average Leave Time	-0.253	0.010	-0.145	-0.065	-0.375***	-0.003	-0.197	-0.066	-0.399*	0.016
	(0.201)	(0.164)	(0.242)	(0.362)	(0.141)	(0.136)	(1.313)	(2.480)	(0.221)	(0.205)
Owner: Clear Channel	0.084	0.101**	-0.049	0.151**	0.105**	0.060	-0.028	0.139***	0.095*	0.070
	(0.060)	(0.043)	(0.062)	(0.062)	(0.053)	(0.047)	(0.050)	(0.036)	(0.050)	(0.440)
Owner: Infinity	-0.026	0.019	-0.117	0.184*	-0.094	-0.039	-0.124**	0.197***	-0.105	-0.018
	(0.080)	(0.095)	(0.091)	(0.106)	(0.066)	(0.063)	(0.062)	(0.072)	(0.071)	(0.089)
Ownership HHI	-0.093	-0.489*	-0.484	0.317	0.169	-0.629*	-0.797	0.965	0.183	-0.619**
	(0.420)	(0.280)	(0.388)	(0.576)	(0.376)	(0.348)	(1.032)	(1.130)	(0.610)	(0.325)
Listenership Asymmetry	0.008	-0.082	-0.280	0.086	0.041	-0.170	-0.158	-0.201	0.022	-0.171
	(0.146)	(0.105)	(0.161)	(0.193)	(0.158)	(0.144)	(0.373)	(0.415)	(0.166)	(0.165)
Market Random Effect	-	-	-	-	1.20E-08	5.30E-11	4.00E-06	6.94E-06	2.55E-07	7.84E-06
Std Deviation					(3.42E-09)	(1.62E-10)	(2.58E-05)	(2.98E-05)	(6.09E-07)	(2.10E-05)
Station Random Effect	-	-	-	-	0.830***	0.842***	0.817***	1.154***	0.821***	0.836***
Std Deviation					(0.039)	(0.046)	(0.291)	(0.301)	(0.039)	(0.048)

Strategic Incentive (α) coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	2.301***	2.747***	0.186	0.074	3.010***	3.348***	0.501	-0.619	0.480	3.443**
(All Stations)	(0.337)	(0.222)	(0.345)	(0.436)	(0.286)	(0.277)	(10.030)	(7.345)	(1.277)	(1.503)
* Market Rank>50	-	-	-	-					1.717	1.222
									(0.746)	(0.703)
* Market Rank>100	-	-	-	-					0.766	0.747
									(0.461)	(0.439)
* Ownership HHI	-	-	-	-					-0.705	-3.108
									(2.804)	(2.253)
* Listenership Asymmetry	-	-	-	-					0.599	-0.561
									(1.082)	(0.962)
Same Format	-	-	-	-	-0.286	-0.240	-0.395	0.624***	-0.183	-0.176
					(0.232)	(0.308)	(0.246)	(0.183)	(0.280)	(0.322)
Log-likelihood	-18817.0	-18370.9	-19210.1	-17101.4	-17736.9	-17330.6	-17239.8	-15328	-17726.8	-17324.1
Number of Station-Hours	27,889	27,574	26,548	25,669	27,889	27,574	26,548	25,669	27,889	27,574

Note: Standard error in parentheses, calculated using a bootstrap which resamples markets. 100 repetitions used for columns 1-8, 25 for columns 9-10.

***,**,* denote significance at the 1, 5 and 10% levels respectively. Observations used are station-hours where the station plays commercials at either :50 or :55 and more than one station is observed in the market.

Table 6: NFXP Estimates

	Model 1 Station and Market Heterogeneity in Probabilities of Choosing :50 or :55				Model 2 Adds Market Heterogeneity in Strategic Incentives				Model 3 Adds Station Heterogeneity in Preferences for :55	
Hour	4-5 pm	5-6 pm	12-1 pm	9-10 pm	4-5 pm	5-6 pm	12-1 pm	9-10 pm	4-5 pm	5-6 pm
$\beta_{:55}$ coefficients										
Constant	0.001	0.002***	0.199***	0.560***	0.001	0.001	0.216***	0.532***	0.001	0.004
	(0.001)	(0.000)	(0.009)	(0.008)	(0.004)	(0.001)	(0.011)	(0.008)	(0.009)	(0.004)
Format Variable	0.005	N/A	-0.417***	-0.932***	0.005	N/A	-0.474***	-0.938***	0.005	N/A
(see notes for definition)	(0.008)		(0.015)	(0.010)	(0.033)		(0.015)	(0.011)	(0.016)	
Station Random Effect, Std Deviation									0.451***	0.412***
	-	-	-	-	-	-	-	-	(0.009)	(0.009)
Strategic Incentives (α)										
Constant	3.304***	3.404***	1.818***	0.476***	0.106	0.200	0.125	0.025	0.107	0.706***
	(0.006)	(0.006)	(0.104)	(0.123)	(0.261)	(0.325)	(0.308)	(0.359)	(0.118)	(0.176)
Market Rank (Linear Effect)	-	-	-	-	0.021	0.010	0.024	0.003	0.021	0.035
					(0.139)	(0.171)	(0.860)	(0.631)	(0.338)	(0.277)
Market Rank ≥ 50	-	-	-	-	1.205***	1.741***	0.119	0.020	1.214***	1.790***
					(0.119)	(0.322)	(0.444)	(0.227)	(0.236)	(0.187)
Market Rank ≥ 100	-	-	-	-	1.563***	1.177***	0.252	0.011	1.574***	0.855***
					(0.171)	(0.102)	(0.437)	(0.332)	(0.194)	(0.160)
Listenership Asymmetry	-	-	-	-	0.099***	0.101***	0.076	0.008	0.100	-0.203***
(normalized mean 0, std deviation 1)					(0.021)	(0.020)	(0.175)	(0.118)	(0.069)	(0.044)
Ownership HHI	-	-	-	-	0.052	0.053	0.053	0.011	0.052	-0.055
(normalized mean 0, std deviation 1)					(0.050)	(0.024)	(0.150)	(0.149)	(0.074)	(0.047)
Market Random Effect, Std. Deviation	-	-	-	-	2.359***	1.183***	1.838***	2.450***	2.165***	0.878***
					(0.201)	(0.050)	(0.168)	(0.168)	(0.090)	(0.051)
Probability that :50 or :55 are chosen										
$\beta_{1 \text{ or } 2}$	0.302***	0.312***	0.139***	0.047***	0.306***	0.294***	0.217***	0.200***	0.309***	0.269***
	(0.009)	(0.005)	(0.009)	(0.010)	(0.018)	(0.009)	(0.011)	(0.013)	(0.006)	(0.007)
Station Random Effect, Std Deviation	0.197***	0.457***	0.257***	0.260***	0.002	0.341***	0.254***	0.237***	0.002	0.025**
	(0.012)	(0.006)	(0.013)	(0.013)	(0.023)	(0.007)	(0.012)	(0.011)	(0.010)	(0.009)
Market Random Effect, Std Deviation	0.397***	0.707***	0.250***	0.319***	0.344***	0.647***	0.294***	0.371***	0.349***	0.402***
	(0.014)	(0.009)	(0.009)	(0.011)	(0.014)	(0.014)	(0.011)	(0.016)	(0.007)	(0.008)
Equilibrium Selection										
λ	0.475***	0.524***	NI	NI	0.520***	0.400***	0.632	0.511	0.524***	0.498**
(NI= not identified when parameters do not support multiple equilibria for any simulation draws)	(0.018)	(0.068)			(0.088)	(0.084)	(0.596)	(0.369)	(0.135)	(0.220)
Log-likelihood	-52,857.60	-52,546.20	-52,712.70	-51,166.70	-52,587.30	-52,307.10	-52,698.50	-51,101.40	-52,326.40	-51,804.00
Number of Station-Hours	50,227	50,103	50,365	49,644	50,227	50,103	50,365	49,644	50,227	50,103

Notes: Standard errors in parantheses. ***,**,* denote statistic significance at the 1, 5 and 10% levels respectively. Estimation by simulated maximum likelihood using a Nelder-Mead search algorithm. Number of simulations per station/market=100 for Model 1 and =50 for Models 2 and 3. Format variable: for 4-5 pm an Oldies dummy, for 12-1 pm and 9-10 pm a dummy for CHR, Rock and Urban stations.

Table 7: Test Results for Within Market Multiple Equilibria

Action 1:	Commercial at :50 or :55	Commercial at :55	Commercial at :55
Action 0:	No Commercial at :50 or :55	No Commercial at :55	Commercial at :50

(a) Modified Likelihood Ratio Test: Proportion of
Markets with Test Statistic Significant at 5% Level (One Sided)

12-1 pm	0.035	0.056	0.049
4-5 pm	0.042	0.014	0.007
5-6 pm	0.028	0.007	0.014
9-10 pm	0.035	0.042	0.014

(b) Station Pairwise Correlation Test: Proportion
of Pairs With Significant Correlations at 5% Level (Two Sided)

12-1 pm	0.058	0.050	0.050
4-5 pm	0.047	0.042	0.049
5- 6 pm	0.051	0.050	0.056
9-10 pm	0.053	0.049	0.045

(c) Station Runs Test: Proportion of
Stations With Significant Runs at 5% Level (Two Sided)

12-1 pm	0.062	0.060	0.047
4-5 pm	0.062	0.050	0.048
5-6 pm	0.064	0.050	0.074
9-10 pm	0.048	0.044	0.050

Table 8: Effect of Different Coordination Incentives on Individual and Equilibrium Strategies

α	Best Response Incentive Change in Choice Probability	Stable Bayesian Nash Equilibrium Strategies	Joint Payoff Maximizing Strategies
0	0	(0.5003,0.4997)	(0.5003,0.4997)
0.5	0.149	(0.5003,0.4997)	(0.5004,0.4996)
1	0.291	(0.5004,0.4996)	(0.5006,0.4994)
1.5	0.422	(0.5005,0.4995)	(0.5025,0.4975)
2	0.537	(0.5006,0.4994)	(0.8297,0.1703)
2.5	0.635	(0.5010,0.4990)	(0.9294,0.0706)
3	0.716	(0.5025,0.4975)	(0.9664,0.0336)
3.35	0.764	(0.5779,0.4221)	(0.9792,0.0208)
3.4	0.770	(0.6259,0.3741)	(0.9806,0.0194)
3.5	0.782	(0.6876,0.3124)	(0.9830,0.0170)
3.75	0.809	(0.7764,0.2236)	(0.9878,0.0122)
4	0.834	(0.8297,0.1703)	(0.9911,0.0089)
4.5	0.874	(0.8933,0.1067)	(0.9953,0.0047)

Table 9: Proportion of Simulated Markets with Multiple Equilibria 4-5 pm

NFXP Model	Markets	Proportion of Simulated Markets with Multiple Equilibria at Estimated Parameters
1	All	0.34
2	Rank 1-49	0.07
2	Rank 50-99	0.17
2	Rank 100+	0.39
3	Rank 1-49	0.03
3	Rank 50-99	0.10
3	Rank 100+	0.27

Table 10: Estimated Values of the Strategic Incentive with Different Sources of Variation in the Degree and Timing of Coordination

Specification	Strategic Incentive Coefficient (Mean and Std Deviation)
1. None	0.12
$\gamma_i^2 = 0, \gamma_m^2 = 0, \lambda = 1, \gamma_{\alpha_m}^2 = 0, \gamma_{\beta_{:55}}^2 = 0$	(0.37)
2. Multiple Equilibria Only	2.49
$\gamma_i^2 = 0, \gamma_m^2 = 0, \gamma_{\alpha_m}^2 = 0, \gamma_{\beta_{:55}}^2 = 0$	(0.14)
3. Variation in Proportion Playing Commercials at :50 or :55 Only	1.91
$\lambda = 1, \gamma_{\alpha_m}^2 = 0, \gamma_{\beta_{:55}}^2 = 0$	(0.34)
4. Station and Market Unobserved Heterogeneity in $\beta_{:55}$ and α Only	3.09
$\gamma_i^2 = 0, \gamma_m^2 = 0, \lambda = 1$	(0.18)
5. Full Model	3.10
estimates from Table 6, Model 3 5-6 pm	(0.20)