The Costs of Product Repositioning: The Case of Format Switching in the Commercial Radio Industry

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Abstract

This paper applies recently-developed methods for estimating dynamic games to estimate the size of costs incurred by radio stations when they change formats (i.e., their positioning in a horizontally-differentiated products industry). The size of repositioning costs potentially affects how markets respond to demand and supply shocks and whether "supply-side substitution" can plausibly constrain market power created by mergers. The paper estimates a rich model of listener demand allowing for the endogeneity of station formats by exploiting timing assumptions similar to those used in the productivity literature. Preliminary estimates indicate that repositioning costs are quite large, and primarily come from the resources that stations have to spend to find new listeners and advertisers.

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1 Introduction

This paper estimates the costs of horizontal product repositioning using data from the commercial radio industry. The paper makes two contributions. First, it quantifies a set of hard-to-measure costs which play an important role in merger analysis in this and other industries, and which affect how markets can be expected to react to demand and supply shocks. Second, it applies the recently developed methods for estimating dynamic games to a setting with significant horizontal product differentiation. One innovation here is that I estimate a rich model of listener demand allowing for product characteristics to be endogenous. This is done using assumptions on the timing of format choices and innovations in unobserved station quality which are similar to those in the production function literature (Olley and Pakes (1996), Blundell and Bond (2000)).

Why should we care about product repositioning costs? In a purely static environment there may be no private or social reason for the set of available products to change. However, in a dynamic environment with demand changes or supply shocks, such as firm closures or mergers, the possibility of product repositioning, which will depend on the size of repositioning costs, may play an important role in determining both the level of consumer welfare and the degree of competition.

The role of product repositioning in affecting competition after mergers is explicitly recognized in the Department of Justice's *Horizontal Merger Guidelines* and the European Commission's *Notice on the Definition of the Relevant Market.* The potential for the merged firm to exercise market power in differentiated product markets can be limited by either demand-side substitution (consumers switching to other products) or supply-side substitution (either through *de novo* entry or existing firms repositioning their products to compete more closely with those of the merged firm). Supply-side substitution can only constrain market power if entry or repositioning costs are small. In industries like radio where demand-side substitution may be limited and new entry is either infeasible (because of spectrum constraints) or prohibitively expensive, supply-side substitution may be the primary constraint on the market power of a firm owning several products which are close substitutes. The small empirical literature examining what happens after mergers also suggests that supply-side substitution plays an important role in constraining market power in practice, e.g., Peters's (2006) analysis of the airline industry and Berger et al.'s (2004) analysis of the banking industry, and that merger analyses based only on static demand-side substitution may lead to misleading policy recommendations.

I provide some preliminary estimates of product repositioning costs using data from the commercial radio industry, where a repositioning is defined by a significant format switch (e.g., a switch from playing Rock music to having Religious programming). The costs of format switching have played an important role in the analysis of radio mergers, and the Department of Justice has challenged many radio mergers which have raised local market-format concentration based on its view that stations in different formats are poor substitutes for advertisers who want to reach particular demographics and that repositioning costs are so large that repositioning would not happen in response to small but significant increases in advertising prices. Repositioning costs are also likely to determine how broadcast radio market respond to supply-side shocks such as licence withdrawal and demand-side shocks such as the migration of certain demographic groups to satellite radio.

Apart from the role that repositioning costs play in merger analysis, there are several data-related reasons why the radio industry provides an almost ideal environment for studying product repositioning. First, broadcast radio stations operate in geographically-distinct local markets so that even though the rate of switching is relatively low (about 4.5% of stations make a significant format switch every six months), there are several thousand examples of major format switches in an 11 year panel. This is almost certainly a larger number of examples of repositioning than could be found in data on any other industry. Second, there are several sources of variation in the data which can help to identify the level and distribution repositioning costs. For example, the incentive to switch into Spanish-language formats will be much larger in markets with large and growing Hispanic populations. The incentive of FM and AM stations to make particular kinds of format switch can also vary considerably based on the relative advantage of the FM signal in contemporary music programming (e.g., the Contemporary Hit Radio/Top 40 and Rock formats). Finally, plausibly exogenous variation in station audiences (coming from e.g., market size and signal coverage) can help to shed light on the source of repositioning costs. For example, suppose that the main cost of format switching was the cost of replacing the station's music library. This cost would be expected to be the same across stations with different audiences, and so we would expect stations which were likely to gain fewer listeners by swithcing, either because of a smaller market size or weaker signal coverage, to be less likely to switch formats.

1.1 Related Literature

1.1.1 Estimation of Dynamic Oligopoly Models

I use a dynamic oligopoly model to estimate format switching costs. A dynamic model is necessary to correctly account for the fact that the payoffs from switching may accrue over a number of years and may also depend on future changes in demand or format changes by competitors.

Several recent papers (Aguirregabiria and Mira (2006), Bajari et al. (2006), Berry et al. (2006) and Pesendorfer and Schmidt-Dengler (2006)) have proposed methodologies for estimating dynamic oligopoly entry and exit-type models with Markov Perfect Nash Equilibria. These approaches build on the insight of Hotz and Miller (1993) and Hotz et al. (1994) that dynamic decision problems can be estimated without solving for equilibrium policies at each step of the estimation process. The two stage estimation approach which I use is closest to those suggested by Hotz et al. (1994) and Bajari et al. (2006, BBL), although I consider various different second-stage estimators which exploit different variation in the data.

Ryan (2005), Collard-Wexler (2005), Ryan and Tucker (2006), Beresteanu and Ellickson (2006) and Maciera (2006) have applied these techniques to actual industry data. Ryan (2005) and Collard-Wexler (2005) examine entry and exit in the homogenous product cement and ready-mix concrete industries. Beresteanu and Ellickson (2006) and Maciera (2006) use logit demand models to allow for a simple form of vertical product differentiation in the supermarket and supercomputer industries. In the radio industry both horizontal product differentiation and vertical product differentiation are important and I use a rich random coefficients demand model to capture these effects. Hitsch (2006) provides a dynamic analysis of new product launches and exit decisions in the ready-to-eat cereal industry, focusing on how individual firms learn about demand for their products.

1.1.2 Demand Estimation with Endogenous Product Characteristics

Standard approaches for estimating demand with differentiated products (Bresnahan (1981), Berry et al. (1995, BLP)) assume that observed product characteristics are exogenous (in particular uncorrelated with any unobserved product attributes). This assumption is obviously inappropriate for an analysis of product repositioning.[1]

One approach to this problem would be to estimate the full product choice equilibrium of the model. This is computationally difficult even in a static setting (Crawford and Shum (2006) for the monopoly case and Draganska et al. (2006) for an on-going attempt in the oligopoly case) and is surely infeasible in the more relevant case of a dynamic model. Instead, I use an approach similar to those taken in the production function literature (Olley and Pakes (1996), Blundell and Bond (2000), Levinsohn and Petrin (2003), Ackerberg et al. (2005)). This literature makes assumptions on the timing of input choices and the process governing innovations in station quality to deal with the problem that productivity and input choices are likely to be correlated. In a demand setting I make assumptions on the timing of format choices and innovations in unobserved station quality. The possibility of this type of approach was recognized in BLP, p. 854 but I am not aware of any previous attempt to use it in the context of demand estimation.

1.1.3 Format Choice in the Radio Industry

There has been some previous work on product positioning in the radio industry. Berry and Waldfogel (2001) and Sweeting (2006) provide reduced-form evidence on the effects of station ownership on

[1] In my setting it is important to estimate the parameters affecting consumers tastes for different product characteristics. If product characteristics are fixed over time and the primary interest is the price elasticity of demand then this can be consistently estimated if the data contains multiple observations on the same product by including product fixed effects (Nevo (2001)).

product differentiation and listenership. Tyler Mooney (2006) estimates a static structural models which suggests stations moved into formats which were more valued by advertisers in the late 1990s. Romeo and Dick (2005) examine the success of format switches in raising station audiences in a small sample of markets. Consistent with my data they find that, on average, stations make small but significant gains in listenership when they switch formats.

1.2 Outline

The paper is structured as follows. Section 2 describes the data. Section 3 presents some stylized facts about format switching which should help to identify the distribution of format switching costs. Section 4 describes the model and Section 5 details the estimation procedure. Section 6 provides some preliminary results and Section 7 concludes.

2 Data

The primary source of data is BIAfn's *MediaAccess Pro* database which contains current and historical data on station characteristics (formats, band, signal coverage etc.), station ownership, Arbitron-measured market shares and BIAfn's own estimates of station and market advertising revenues. I use data from the Spring and Fall quarters as some markets are only rated in these quarters. The revenue data is used to form an estimate of the average value of a listener in a market. I have data covering the period Spring 1996 to Spring 2006 from the 2001, 2002 and 2006 versions of the BIAfn database. There is a lot of missing data for 1996 so I use data from 1997 onwards.[2] There is no ratings data for non-commercial stations and I only use data on commercial stations in the analysis.[3]

[2] Some gaps in the BIAfn data, including data on stations leaving the industry before 2001 were filled in using old editions of Duncan's *American Radio*.

[3] The demand specification includes market-format fixed effects so that ignoring non-commercial stations which stay in the same format such as News should not cause a major problem.

2.1 Formats

I use the ten format categories listed in Table 1 to categorize each station's programming. The BIAfn database has 20 format categories and I combine those categories which have similar programming (for example, the playlist data used in Sweeting (2006) shows that Rock and Album Oriented Rock/Classic Rock stations play similar songs) and appeal to similar demographics as the costs of switching between these formats is likely to be small. The ten remaining formats clearly appeal to different demographic groups based on age, sex and ethnicity/race. Contemporary music formats, such as Adult Contemporary, CHR/Top 40, Rock and Urban, are dominated by FM stations, while AM stations are more numerous in the News/Talk, Other Music and Religious formats. I also define another format "Dark" for stations which are off-air in any particular period.

2.2 Geographic Markets and Demographic Data

Local radio markets are defined using Arbitron's market definitions. These are also used by the FCC and the Department of Justice. There are over 280 markets in the full dataset. Some radio markets are close together (e.g., Boston and Providence, RI) so that stations may be rated in multiple markets. While the decision of out of market stations to switch formats can be helpful in identifying home market stations incentives to switch formats, keeping track of interactions between markets complicates estimation. In estimating the structural model I therefore use a subset of markets where out of market stations play a small role.

Table 1 shows that demographics have large effects on demand for different formats. Local market demographics (age, sex and ethnicity/race combinations) are measured using the US Census's Annual County Population Estimates aggregated to the market level.[4]

[4]The estimates come from July of each year, so I interpolate to give numbers for the Spring and Fall quarters. Counties are matched to markets using Arbtiron's 2005 market definitions which are changed rarely.

2.3 Listenership

The BIAfn database reports Arbitron data on station listenership. Arbitron estimates are based on diaries completed by a sample of listeners. I use two types of station level share data. The first type is the "AQH Share" which measures the station's share of radio listening by people aged 12 and above during a broadcast week of Monday-Sunday 6am-midnight. The AQH share numbers are multiplied by the market APR (the proportion of the 12+ population listening to any radio) to generate station market shares for demand estimation. The market is therefore defined by the total time available to the 12+ population during the broadcast week. Listenership to non-commercial stations, which are not rated in Arbitron's standard reports, is included in the outside good.[5]

One issue that arises is that almost 25% of home market commercial stations have too few listeners to meet Arbitron's Minimum Reporting Standards (typically around 0.3% of radio listening) in any given quarter even though they are on air (i.e., there is a significant tail of very small stations). Dropping these stations could affect the estimated substitution patterns if, in a particular market, they are concentrated in certain formats but, on the other hand, it is obviously undesirable to have imputed market shares having too much effect on the final estimates. I currently address this issue by dropping those stations that do not meet the Minimum Reporting Standard in over half the quarters in the data and imputing a share for the rest based on the number of quarters for which they have missing data and the share of the smallest reported station. I include a dummy for these stations in estimating the demand model. Future versions will check whether the results are robust to this treatment.

Total radio listenership has declined since the late 1980s reflecting, for example, the availability of CDs and other types of electronic entertainment. The rate of decline has been very similar across markets. In general, it is difficult to estimate dynamic models where there is a significant trend in the data because of the possibility that firm strategies will look quite different in the future where

[5] The conversion is done using Arbitron's market-quarter APR numbers taken from Duncan's American Radio up to 2001, M Street's STAR database for 2002 and Spring 2003 and from additional data provided by BIAfn from Fall 2004. For the two missing numbers I simply interpolate between the missing quarters. This is reasonable as APR numbers change relatively little from quarter to quarter.

the state variables are different. In the present version I remove the national time trend from the listenership data before estimating the model. One justification for doing this is that even though radio listenership is declining, the size of the radio industry measured in dollars has remained pretty much the same since 2000, increasing by an average of less than 1% per year (estimates reported on the Radio Advertising Bureau's website).

The second type of station-level share data is demographic specific share data for different age/sex groups in Spring 2006. This data is very useful in identifying demographic preferences for different formats, but there is a lot of missing data for smaller stations. I use these numbers to calculate station shares for 6 mutually exclusive age/sex specific groups (12-24, 25 to 49 and 50+ for men and women).

There is no station-level share data for ethnic/racial listening. However, Arbitron website does provide two types of data useful for identifying ethnic/racial format preferences. The first type is market-specific estimates of total time spent listening by blacks and Hispanics in Fall 2004. The second type is estimates of the average proportion of station listeners who were black or Hispanic by format in Spring 2003, 2004 and 2005, based on data for a specific set of markets.

2.4 Station Entry and Exit

I treat the number of stations in a market as fixed but allow stations to switch into and from the inactive Dark format. Ignoring the margin of *de novo* entry is a reasonable approximation in this industry.[6] Entry is severely limited by both spectrum constraints, especially in larger markets, and by the need to secure an FCC licence (with several thousand applications per approval). In the largest 200 radio markets there were 230 entries by commercial stations in the decade after 1997 (compared with 4,395 active stations) and only a handful of these entering stations gained significant listenership, partly because their signals typically had limited coverage. I treat entering stations as being in the Dark format until they enter. There are 37 cases of exit during the same period, with most of these

[6] There is also the margin of small stations which are currently rated by Arbitron growing larger to become significant competitors. In the current version this margin is also being ignored.

being due to FCC licence withdrawals.[7]

2.5 Ownership

The BIAfn database provides an ownership history for each station. Many radio companies own multiple stations, either in the same market or in different markets. There has been substantial growth in common ownership since the 1996 Telecommunications Act relaxed the rules limiting how many stations a single firm can own. Specifically, a single firm can own up to 8 stations in a single market (the limit varies with market size) and an unlimited number of stations across markets. The largest owner, Clear Channel Communications, owns more than 1,200 stations across the country although it has recently announced the sale of over 400 of its stations in smaller markets. It is quite plausible that common owners are able to realize economies of scale or scope from operating stations in the same format, either within markets or across markets. In the current version I abstract from common ownership. The main difficulty in modelling common ownership is how to model stations' expectations about common ownership may change in the future.

3 Five Stylized Facts About Format Choices and Format Switching

This section summarizes several stylized facts about format switching and format choices which are both important to allow for and which may help to identify the distribution of format switching costs. These facts are based on data from 196 of the largest 200 Arbitron radio markets excluding markets added by Arbitron after 1997.

1. AM and FM stations exhibit different switching patterns. Table 2 provides some summary statistics on station format and format switching choices based on those home market stations with enough listeners to be rated by Arbitron. On average, about 4.6% of stations switch formats from quarter-to-quarter with over 3,800 switches observed in the data. All formats experience entry

[7] Note that these cases of entry and exit do not include cases where a construction licence is granted but the station is never built, so that the licence is forfeited again.

and exit, with the Spanish format having the greatest amount of net entry.

The table distinguishes between AM and FM stations. FM stations are much more likely to switch to the Adult Contemporary, Contemporary Hit Radio and Rock formats, presumably because of the FM signal's advantage in these formats. AM stations are disproportionately likely to switch to News/Talk and, to a lesser extent, Other Music. These differences can help to identify the distribution of format switching costs in the following way: suppose that I can estimate the difference in the expected future payoffs (in \$s) of an AM station and an FM station to making a particular switch. As the variance of the switching cost distribution increases this payoff difference should have less effect on switching patterns.

2. Average station listenership differs across formats. The "relative share" column in Table 2 shows that the average number of listeners per station differs across formats (calculation explained beneath the table). For example, Urban and CHR/Top 40 stations tend to have more listeners than Rock stations. The obvious explanation is that the average Rock listener (white, male, aged 25-49) is more valuable to advertisers than the average Urban listener (black) or CHR/Top 40 listener (younger), so that for the same expected listenership it is more attractive for a station to enter the Rock format. The small relative listenership of Spanish stations may be explained by the expected future growth of Hispanic populations or by these stations having some form of market power by catering to listeners not easily reached by other media. The small number of listeners per Religious station may reflect these stations being able to receive additional revenues through other sources (e.g., donations) or by being able to use relative cheap programming (e.g., broadcast of religious services).

3. Switchers have fewer listeners than non-switchers and gain listeners when they switch. Table 3 compares the market shares of switching and non-switching stations. On average, switching stations have 34% fewer listeners than non-switchers before they switch and they tend to increase their listenership by a statistically significant 13% in the year (two quarters) following the switch. This is consistent with stations switching formats to gain share and requiring moderate expected gains in listenership in order to switch.[8]

It is also notable that the standard deviation in the change in share for switchers is only 29% greater than the change in share for non-switchers. One might have expected uncertainty about how a station would perform in its new format together with the different competitive environment to lead to much more volatile changes in share. The listenership of larger, non-switching stations tend to falls both because they lose listeners to switchers but also because there is a pattern that the listenership of larger stations tends to decline and the listenership of smaller stations increases.

4. Switching rates similar across markets of different sizes. Figure 1 plots the rate of format switching in each market against the log of market population and average station listenership in 2001. The switching rate does not vary systematically with either variable. This suggests that the costs of finding new listeners or advertisers, which might increase with market size or station audiences, are likely to be a more important component of switching costs than costs such as replacing a station's music library which should be the same across markets.

5. Observable market demographics affect format choices and format switching. Tables 4(a) and (b) reports the results of regressions which investigate how far observable market features can explain (changes in) the distribution of stations across formats. The regressions in Table 4(a) are between-market regressions where the dependent variable is the proportion of home market stations in a particular format and the independent variables are a set of market demographics, region dummies and the combined share of out of market stations. This variable is included to test whether home market stations avoid formats where there is significant competition from out of market stations. As the out of market share may be endogenous I instrument for it using a predicted share based on share

[8] One might be concerned that the pattern where switchers gain shares may simply reflect a pattern where all stations with few listeners tend to gain share even if they do not switch formats. I have therefore also compared the share increase of switchers with the share performance of non-switchers who are matched to the switchers based on their share prior to switching. The matched non-switching comparison group do experience falls in listenership which are smaller than the falls for the non-matched non-switching group used in Table 3 but they are still significantly different from the increases in listenership experienced by the switching stations.

in other markets.[9]

The coefficients show a sensible pattern, although the age-sex coefficients are largely insignificant because these variables vary little across markets. There are more Urban and Religious (Gospel), and fewer Country, stations in markets with larger black populations, and more Spanish stations in markets with more Hispanics. The region dummies indicate that there are more Country and Religious stations in the South than in New England. Four out of the ten out of market share coefficients are negative and statistically significant at the 10% level while none are positive and significant. This is consistent with home market stations being less likely to enter or stay in a format where they face significant competition from out of market stations.[10]

Table 4(b) reports the results of similar within-market regressions. I do not include the age and sex variables, which vary little within markets over only a ten year time period, although including them has only a small effect on the ethnic/race and out of market share coefficients. The ethnic/race coefficients have a similar pattern to those in the between market regressions (except the large negative effect of growing black populations on Oldies stations) indicating that changes in the ethnic composition of markets lead to format switching in the expected directions. Five out of the ten out of market coefficients are negative and significant and only one (Other Music) is large, positive and significant. When the formats are pooled and the out of market coefficient is assumed to be the same across formats the coefficient is negative and significant at the 5% level.

[9] I create the instrument in the following way: I calculate the average (across quarters) share of listening in each market to stations which are home to every other market. I then find each station's average (across quarters) share of listening in its home market. I multiply these two numbers together to calculate the predicted share of each out of market station. I then add the predicted shares of all of the out of market stations in a category to create the instrument. This instrument implicitly assumes that an out of market station's choice of format does not depend on the number of home market stations in a format. This may not be completely true in situations where stations in both of the markets have significant listening in the other market, but it is much more likely to be true in situations where the out of market stations are located in a large market (e.g., Boston) where stations from a nearby smaller market (e.g., Worcester) have almost no listening.

[10] If there are local tastes for a format which are common across nearby markets and which are not captured by the region dummies then this would tend to provide a positive bias to these coefficients.

4 Dynamic Model of Format Switching

This section presents the model of listener demand and station format choice.

4.1 State Space

The state space is composed of (i) a set of station, market and format characteristics which are observed by all stations when they make their format switching decisions and which are observed or can be estimated by the econometrician (denoted $\mathcal{S}$ in what follows), and (ii) a set of iid private information payoff "shocks" that affect a station's payoff from making format choices in a particular period. These shocks can be interpreted as reflecting heterogeneity in format switching costs, but they also act more generally as the unobservable affecting format switching decisions.

4.1.1 Station Characteristics

There are N_m stations in market m. Every station is in exactly one format in each quarter. There are eleven available formats (F): the ten formats listed in Table 1 and the inactive "Dark" format (0). Stations has a fixed quality which is the same across formats, based on several observable variables (signal coverage, power, age, out of market status and a dummy for whether the station is too small in some quarters to be rated by Arbitron). Each station has a band (AM or FM) which determines a format-specific quality component. Each station also has a quality component ξ_{smt} which can evolve over time. This is not directly observed from the data but can be estimated.

4.1.2 Market Characteristics

The population in each market is made up of 18 mutually exclusive age-sex-ethnic/race groups. The ethnic/racial groups are non-Hispanic whites, non-Hispanic blacks and Hispanics. As age-sex ratios differ relatively little over time within markets, I model each ethnic/racial group as having a particular growth rate which can evolve over time. Each market is also associated with a particular advertising price per listener and each format in each market has a particular attractiveness γ_{mf} which is assumed to be fixed over time.

4.2 Timing

There are an infinite sequence of periods, corresponding to the Spring and Fall ratings quarters. In each quarter the timing of the game is as follows:

1. stations observe current station qualities, formats, market demographics and the attractiveness of each format;

2. each station observes random shocks (ε) to its payoffs from choosing to be in a particular format in the next quarter. These shocks are iid across stations, formats and time and are private information to the station. Having observed its εs, each station simultaneously decides which format to be in the next quarter;

3. listeners choose which station to listen to based on current station qualities, formats and the attractiveness of each format. Station payoffs (advertising revenues, switching costs) for the current quarter are realized; and,

4. station formats change according to station format choices. Other features of the state space, including the unobserved station qualities, evolve according to the stochastic processes described below.

4.3 Evolution of the State Space

Station formats change from quarter-to-quarter with station format choices. Station qualities and market demographics evolve according to stochastic processes.

4.3.1 Station Quality

Unobserved (to the econometrician) station qualities evolve according to a stationary AR(1) process. Specifically, I assume that for a station which does not change formats

$$\xi_{smt} = \rho^{\xi} \xi_{smt-1} + \nu_{1smt} \tag{1}$$

where $\nu_{1smt} \sim N(0, \eta_1^{\xi})$. The absence of a constant reflects the fact that mean unobserved quality is normalized to be equal to zero. For a station changing formats I assume that

$$\xi_{smt} = \rho^{\xi} \xi_{smt-1} + \mu_2^{\xi} + \nu_{2smt} \tag{2}$$

with $\nu_{2smt} \sim N(0, \eta_2^{\xi})$ so that the quality change for a format switcher may be drawn from a different distribution.

A comment is in order about this specification. An unobserved and time-varying component of station quality is necessary to rationalize the listener share data because station shares can change in ways which could not be explained by changes in demographics even without format switching. ξ_{smt} increases when a station's programming becomes more attractive to listeners (either because of changes in programming or changes in tastes). It would, of course, be desirable to explicitly model the investment process through which a station might try to (stochastically) affect ξ_{smt}, but this is very difficult to do without data on investment spending.[11]

The assumption of a single scalar unobservable following an AR(1) process is restrictive, but as I explain in Section 5.2.1, while it is unnecessary for the estimation of demand it is necessary for the more complete dynamic model.

[11] If one did model the investment process then the estimation strategy below could be adjusted to use moments based on unexpected innovations in station quality (e.g., investments in quality which turn out to be better than expected).

4.3.2 Market Demographics

I assume that the growth rate of each ethnic/racial group follows an AR(1) process:

$$g_{emt} = \rho^e g_{emt-1} + \mu^e + \nu_{emt} \tag{3}$$

where $\nu_{emt} \sim N(0, \eta^e)$. With $\rho^e < 1$ this implies that the growth rate of each population group is stationary with mean $\frac{\mu}{1-\rho^e}$ and variance $\frac{\eta^e}{(1-\rho^e)^2}$. I assume that the same process applies to each population group so that in the long-run the proportion of the population in each ethnic group is also stationary. However, a high value of ρ^e implies that the rapid growth of Hispanic populations in some markets tends to persist for some years into the future.

4.4 Station's Static Payoff Function

Each quarter a station earns revenues which depend on its listenership and its format switching decision. Formally the payoff in quarter t for a station s in market m and format f_{st} which decides to switch to format f_{st+1} is

$$\pi_{smt}(f, g, \mathcal{S}, \varepsilon_{st}, \theta) = \left(p_m \sum_{d=1}^{D} \theta_d l_{sdt}(\mathcal{S}) \right) - I(f_{st} \neq 0)\theta_2 - I(f_{st+1} \neq f_{st}, f_{st+1} \neq 0)\theta_3 + \varepsilon_{st}(f_{st+1}) \tag{4}$$

where $l_{sdt}(\mathcal{S})$ is the number of listeners the station has in demographic group d and p_m is the average "price" of a listener in market m.[12] The θ_d parameters allow the relative value of listeners to vary across demographics (and possibly formats). θ_2 measures the fixed cost associated with being active (not being Dark). The parameter θ_3 measures the cost of switching to a different active format. I consider various parameterizations of this switching cost below e.g., allowing it to vary with the type of switch made, market size, the price of advertising in the market. Future versions will consider how it

[12] I assume that stations only get revenues from their home market listenership. While this will not be exactly true, it is a reasonable approximation for most stations. On average, a station rated in multiple markets has around 80% of its listeners in its home market and regressions using BIAfn's station-level revenue estimates indicate that an additional out of market listener generates around 20% of the revenue of an additional home market listener.

varies with station ownership. $\varepsilon_{st}(f_{st+1})$ is a random term affecting a station's payoff from choosing to be in format f_{st+1} in the next period. It is assumed to be iid across stations, format choices and time and to be drawn from an extreme value (Gumbel) distribution with location parameter 0 and scale parameter σ. The scale of σ is identified because knowledge of advertising prices allow everything to be put in dollar terms. The most obvious interpretation of the εs is that they reflect heterogeneity in format switching costs although a station also receives an ε if it decides to remain in its current format.

4.5 Listener Demand

I model listener demand for stations using a random coefficients logit model. The market consists of listeners aged 12 and above. Each listener chooses to listen to at most one commercial radio station. The utility listener i in market m receives by choosing station s in quarter t is

$$u_{ismt} = \gamma_i^C + F_{smt}\gamma_{imt}^F + X_{sf_st}\gamma^S + \xi_{smt} + \varepsilon_{ist} \tag{5}$$

where F_{smt} is a row vector indicating the current format of station s and ε_{ist} is the standard logit error. γ_i^C allows for heterogeneity in utility from listening to commercial radio and I assume that $\gamma_i^C \sim N(0, \sigma_C^2)$. γ_{imt}^F is individual i's taste for a stations in formats F and I assume that

$$\gamma_{imt}^F = \overline{\gamma_m^F} + \Gamma^A A_i + \Gamma^E E_i + \Gamma^S S_i + \Sigma v_i^F \tag{6}$$

$\overline{\gamma_m^F}$ is a vector of market-format fixed effects which accounts, for example, for the presence of significant non-commercial competitors in some formats in some markets. Γ^A, Γ^E and Γ^S are the additively separable effects of age, ethnicity/race and sex on format preferences. The v_i^Fs, assumed to be drawn from a standard normal distribution, create random variation in format tastes across individuals with the same demographics. Σ is assumed to be diagonal so that any correlations across tastes for different formats are assumed to be sufficiently accounted for by demographics and the market-format fixed effects.

X_{sf_s} contains the fixed, observed characteristics of station s, such as its signal coverage, as well as a set of FM band-format interactions to allow FM stations to be more valuable in some formats. All listeners are assumed to value these characteristics and ξ_{smt}, the unobserved quality component, in the same way.

4.6 Equilibrium Concept: Markov-Perfect Nash Equilibrium

I follow the recent literature on the estimation of dynamic games by assuming that stations play a symmetric, anonymous, stationary, pure strategy Markov Perfect Nash Equilibrium. This is an assumption on the existence of this type of equilibrium as well as on the assumption of which type of equilibrium, if there are several, is actually played by stations.[13] To be clear, I treat stations as individual profit-maximizing entities ignoring the effects of common station ownership.

Formally, a station's stationary Markov Perfect strategy is a function ς_s which maps from the observable state space and the station's own current payoff shocks (the ε_ss) to actions (format choices), i.e., $\varsigma_s : \mathcal{S} \text{ x } \varepsilon_s \rightarrow A_s$. A profile of Markov Perfect strategies for all stations is $\varsigma = (\varsigma_1, \varsigma_2, ...)$, $\varsigma : S \text{ x } \varepsilon_1 \text{ x } \varepsilon_2 \text{ x } .. \rightarrow A$. Prior to the realization of its ε_ss a station's strategy implies a probability distribution over format choices in the current quarter.

A station's value function prior to the realization of its ε_s is

$$V_s(\mathcal{S}|\varsigma_s) = E_\varepsilon \left[\pi_s(\mathcal{S}, \varsigma_s(\mathcal{S}, \varepsilon_s)) + \beta \int V_s(\mathcal{S}'|\varsigma_s) dP(\mathcal{S}'|\varsigma(\mathcal{S}, \varepsilon), \mathcal{S}) \right] \tag{7}$$

where β is the common discount factor, $\pi_s(\mathcal{S}, \varsigma_s(\mathcal{S}, \varepsilon_s))$ are static payoffs as a function of the state

[13] Dorazelski and Satterthwaite (2003) examine the existence of equilibria of this type in dynamic oligopoly models. One obvious difference between my model and the stylized model that they consider is that I treat station qualities, population proportions and growth as being continuous rather than discrete. One could obviously map my model into a model with a discrete state space by considering an arbitrarily fine discretization of the continuous variables. A further issue concerns the stationarity of the state variables. I find that, on average, market populations are growing and this tends to increase station revenues given a fixed number of stations (although much more slowly than discounting reduces the value of future profits). On the other hand, growth rates and the proportion of the population in each demographic group are stationary and it is these growth rates and proportions which determine the relative profits that can be made in different formats. Ellickson and Beresteanu (2006) discuss similar issues that arise in their analysis of the dynamics of supermarket oligopolies.

space and a station's own strategy and $P(S'|\varsigma(S,\varepsilon),S)$ is the probability that the state in the next quarter will be $\mathcal{S}'$ given a current state $\mathcal{S}$ and station strategy profiles ς. For ς_s^* to be optimal it must provide s with a higher expected value than alternative strategies at all points in the state space.

$$V_s(\mathcal{S}|\varsigma_s^*) \geq V_s(\mathcal{S}|\varsigma_s) \quad \forall \mathcal{S}, \varsigma_s \tag{8}$$

A profile of strategies ς^* is a Markov Perfect Nash Equilibrium if each station's strategy is optimal given the strategies of other stations.

5 Estimation

This section outlines the estimation procedure. I use a two stage estimation procedure similar to that proposed by Hotz et al. (1994) and BBL. Listener demand, demographic transitions and station conditional format choice probabilities are estimated in the first stage. The second stage uses the first-stage estimates and forward simulation to estimate the parameters of the payoff function (4). Consistent with most of the literature in this area I do not estimate the discount factor but instead assume that it is 0.95.[14]

5.1 First Stage: Demographic Transitions

Equation (3) is estimated using the market demographic data described in Section 2.[15] To prevent some very small ethnic/racial groups, which occasionally show large proportional changes, having an excessive effect on the estimates, I only use observations on those groups with at least a 5% share of

[14] There is variation in the data which could potentially identify the discount rate. For example, if stations are willing to switch into the Spanish format when the Hispanic population is smaller but its growth rate is higher then it must be the case that stations are giving weight to future profits. However, estimating the discount factor complicates the second stage of the estimation process and I do not attempt it in the current version.

[15] Although I estimate the rest of the model using a subset of 40 markets, I estimate the demographic transitions using data from the 200 largest Arbitron markets.

market population.[16] The estimated parameters are

$$g_{emt} = \underset{(0.025)}{0.856} g_{emt-1} + \underset{(0.000)}{0.001} + \nu_{emt} \tag{9}$$

and the standard deviation of ν_{emt} is 0.0048 (0.0012). This implies that the average long-run growth rate is 0.7% per half-year.

Figure 2 shows how the population of Bakersfield, CA changes when I simulate forward using this model of population growth. While the growth rates of the different population growths tend to converge over time, on average the Hispanic population overtakes the non-Hispanic white population in 2014.

5.2 First Stage: Listener Demand

The listener demand model is estimated using a Generalized Method of Moments procedure using four sets of moments.

5.2.1 Quasi-Differenced Demand Moments

The "mean utility" of station s in market m at time t is

$$\delta_{smt} = F_{smt}\overline{\gamma_m^F} + X_{sf_s}\gamma^S + \xi_{smt} = \widetilde{X_{smt}}\Gamma^L + \xi_{smt} \tag{10}$$

where Γ^L are the linear parameters of the demand system. An endogeneity problem arises if the unobservable component of station quality ξ_{smt} is correlated with station format choices. For example, stations of higher unobserved quality may choose to be in formats which are more popular with listeners. I now explain how my assumptions on the timing of station format choices and the process governing innovations in unobserved quality allow me to deal with the endogeneity issue.

[16] The jumps in proportions for small groups may be partly generated by the census updating the basis of its annual estimates.

Recall that for a station remaining in the same format

$$\xi_{smt} = \rho^{\xi}\xi_{smt-1} + \nu_{1smt} \tag{11}$$

and that, because ν_{1smt} is realized after the format choice for time t is made, ν_{1smt} should be uncorrelated with $\widetilde{X_{smt}}$. ν_{1smt} is isolated by taking a quasi-difference

$$\nu_{1smt} = \xi_{smt} - \rho^{\xi}\xi_{smt-1} \tag{12}$$

$$= (\delta_{smt} - \rho^{\xi}\delta_{smt-1}) - \left(\widetilde{X_{smt}} - \rho^{\xi}\widetilde{X_{smt-1}}\right)\Gamma^{L} \tag{13}$$

For stations which change formats the unexpected innovation in station quality is

$$\nu_{2smt} = \xi_{smt} - \rho^{\xi}\xi_{smt-1} - \mu_2^{\xi} \tag{14}$$

$$= (\delta_{smt} - \rho^{\xi}\delta_{smt-1}) - \left(\widetilde{X_{smt}} - \rho^{\xi}\widetilde{X_{smt-1}}\right)\Gamma^{L} - \mu_2^{\xi} \tag{15}$$

These innovations can be used to form moment conditions

$$E[Z_{smt}\widehat{\nu}_{smt}(\Gamma)] = 0 \tag{16}$$

For each value of the non-linear demand parameters (the demographic and random taste coefficients and ρ^{ξ}), I solve for the δs using the contraction mapping procedure proposed by Berry et al. (1995). For each demographic group I use 50 sets of Halton draws for the random components of tastes and weight each demographic group appropriately to compute the aggregate market share.[17] The linear parameters can be conditioned out so that the search is restricted to the non-linear parameters. Analytic derivatives are used to speed the search, as suggested by Nevo (2001).

The instrument matrix includes all of the observable period t and $t-1$ station characteristics,

[17] Different Halton draws are used for each demographic group so that there are 900 Halton draws in total.

together with demographic variables interacted with format dummies and counts of the number of other stations in each format. These latter variables should be correlated with the derivatives of δ with respect to the non-linear parameters. The share of a station in $t-1$ is also included as an instrument to help to identify ρ^{ξ} it should be correlated with δ_{smt-1}. As ρ^{ξ} increases the role of time-series variation in identifying the parameters will tend to increase.

Alternative Assumptions on Station Quality The structural and dynamic panel production function literatures have used timing assumptions to circumvent the problem that labor and capital may be correlated with unobserved firm productivity. However, these literatures have generally made more flexible assumptions on unobservable productivity than I am making on unobservable station quality here. In this sub-section I briefly describe these alternative assumptions and explain why it is not possible for me to make them in the context of a dynamic oligopoly model.

In the dynamic panel data literature (e.g., Blundell and Bond (2000)) the productivity residual is typically allowed to have three error components

$$\psi_{it} = \alpha_i + \xi_{it} + \varepsilon_{it} \tag{17}$$

where α_i is a fixed firm-specific productivity effect, ξ_{it} is a serially correlated productivity effect and ε_{it} is an iid shock which may represent measurement error in output. Typical assumptions are that ξ_{it} follows an AR(1) process, $\xi_{it} = \rho\xi_{it-1} + \nu_{it}$, and that α_i and ξ_{it} may be correlated with labor and capital but that ε_{it}, which may just represent measurement error in output, is not. As pointed out by Ackerberg et al. (2006) an innovation which should be uncorrelated with capital and labor can be formed by taking a "difference in quasi-differences"

$$(\psi_{it} - \rho\psi_{it-1}) - (\psi_{it-1} - \rho\psi_{it-2}) = (\nu_{it} - \nu_{it-1}) - (\varepsilon_{it} - \rho\varepsilon_{it-1}) - (\varepsilon_{it-1} - \rho\varepsilon_{it-2}) \tag{18}$$

I could allow for a similar error structure in mean utility when estimating demand, although using a moment condition like (18) is obviously even more demanding of the data. However this approach does not allow α_i and ξ_{it} to be recovered, preventing the application of techniques for estimating the dynamic model which assume that station qualities are part of the state space observed both by firms and the econometrician. Of course, it should be possible to use this richer specification as a robustness check on the demand parameters.

In the structural production function literature (Olley and Pakes (1996), Levinsohn and Petrin (2003)) it is standard to allow for a single scalar unobservable productivity shock which is correlated with inputs (similar to my ξ_{it}) but which can follow a first-order Markov process which is more general than AR(1), together with an ε_{it} which is not correlated with input choices. However, this literature assumes that ξ_{it} is monotonically related to another observed variable (investment in Olley-Pakes and an intermediate input such as materials in Levinsohn-Petrin) and that this relationship can be inverted to find the values of ξ_{it} which can then be controlled for in estimating the parameters. The problem with using this approach is the lack of a suitable additional variable in my setting.[18]

5.2.2 Demographic Moments

The three further sets of moments help to identify the demographic taste parameters. The first set match the proportion of a station's audience in each of six age-sex specific demographic groups to those reported in the station-level Arbitron data for Spring 2006,

$$E[Z_{dsmt}(\widehat{P_{dsmt}(\Gamma)} - P_{dsmt})] = 0$$

where P_{dsmt} is the proportion from demographic group d observed in the data. Z_{dsmt} is simply an indicator for whether the station-observation has information for demographic group d reported. These moments are similar in spirit to the micro-moments used by Petrin (2002), although my proportions

[18] A candidate in many demand contexts would be price as given parameters the first-order pricing relationships implied by equilibrium pricing behavior can be used to impute a value of ξ_{it} if there is assumed to be no unobserved heterogeneity in marginal cost. Note that radio is one industry where the assumption of no heterogeneity in marginal costs might be acceptable as the costs of selling commercial time are largely be fixed (having a sales staff and the facility to produce commercials).

are station-market-time specific.

I do not have station-level data on ethnic/racial listening. However, I form moments which match the average proportion of listeners who are black/hispanic for stations in each format to those reported by Arbitron for Spring 2003, 2004 and 2005,

$$E[Z_{esmt}(\widehat{P_{esmt}(\Gamma)} - P_{eft})] = 0$$

where Z_{esmt} is an indicator for whether station s is in format f and whether market m at time t was one of the markets used by Arbitron to calculate their reported sample proportions.

The final set of moments match total time spent listening by blacks and Hispanics to those reported by Arbitron for a set of markets in Fall 2004,

$$E[Z_{emt}(\widehat{TSL_{emt}(\Gamma)} - TSL_{emt})] = 0$$

where Z_{emt} is an indicator for a reported market.

5.2.3 Objective Function

I stack the different sets of moments to give a vector of moments $G(\theta)$, including the simulated moments. The objective function is

$$\min_{\theta} G(\theta)'WG(\theta)$$

where W is a weighting matrix. I use a two-step procedure, following Hansen (1982), where in the first step W is simply the identity matrix and in the second step it is an estimate of the inverse of the variance-covariance matrix of the various moments calculated using the consistent parameter estimates from the first step.[19]

[19] W is block-diagonal because the different groups of moments (quasi-differenced, ethnic/racial TSL, ethnic/racial format listening, conditional choice probabilities and forward simulation) come from different sampling processes.

5.3 First Stage: Station Conditional Choice Probabilities

The Markov Perfect Nash equilibrium assumption implies that equilibrium station format choice probabilities should be functions of the observed state variables, such as local demographics, current station qualities and local format preferences. Ideally these functions should be estimated non-parametrically. As in Ryan (2006), Ryan and Tucker (2006) and Beresteanu and Ellickson (2006), the size of the state space require me to be more restrictive, and I assume that the conditional choice probabilities can be adequately approximated using a rich multinomial logit model where the explanatory variables are rich functions of the state variables.[20]

5.4 Second Stage: Estimation of the Payoff Parameters

The second stage estimates the parameters of the payoff function (4) including format switching costs. Given current state $\mathcal{S}$, realized payoff shocks ε_s and station policies ς the expected discounted payoffs of a station s at time $t=0$ in format f_{s0} choosing to be in format f_{s1} in the next quarter are

$$
\begin{aligned}
&\Pi_{s0}(\mathcal{S}_0, \varsigma^*, \theta_2, \theta_3, \sigma, f_{s1}) + \varepsilon_{s0}(f_{s1}) \\
&\sum_{d=1}^{D} p_m \theta_d l_{sd0}(\mathcal{S}_0) + E_{\varsigma_s^*, f_{s1}, \varsigma_{-s}^*} \sum_{t=1}^{\infty} \beta^t \sum_{d=1}^{D} p_m \theta_d l_{sdt}(\mathcal{S}_t) - \left(I(f_{s0} \neq 0) + E_{\varsigma_s^*, f_{s1}, \varsigma_{-s}^*} \sum_{t=1}^{\infty} \beta^t I(f_{st} \neq 0) \right) \theta_2 \\
&- \left(I(f_{s0} \neq f_{s1}, f_{s1} \neq 0) + E_{\varsigma_s^*, f_{s1}, \varsigma_{-s}^*} \sum_{t=1}^{\infty} \beta^t I(f_{st} \neq f_{st+1}, f_{st+1} \neq 0) \right) \theta_3 + E_{\varsigma_s^*, f_{s1}, \varsigma_{-s}^*} \sum_{t=1}^{\infty} \beta^t \varepsilon_{st}(f_{st+1}) + \varepsilon_{s0}(f_{s1})
\end{aligned}
\tag{19}
$$

where $E_{\varsigma_s^*, f_{s1}, \varsigma_{-s}^*}$ denotes the expectation given that station s chooses to be in f_{s1} in period $t=1$ and will use its equilibrium strategy ς_s^* in the future and all other stations will use their strategies ς_{-s}^* both in the current period and in the future. σ (the scale parameter of the distribution of ε) enters as it affects the expected future values of the εs reflecting different choices. The probability that format f_{s1} is chosen, given the assumption that ε is distributed extreme value with location parameter 0 and

[20] Ryan (2006), Ryan and Tucker (2006), Beresteanu and Ellickson(2006) all use similar types of approach to estimate conditional choice probabilities in dynamic models.

scale parameter σ, is given by the multinomial logit formula

$$\Pr(f_{s1}|\mathcal{S}_0, \varsigma, \theta_2, \theta_3, \sigma) = \frac{\exp \frac{\Pi_{s0}(\mathcal{S}_0, \varsigma, \theta_2, \theta_3, \sigma, f_{s1})}{\sigma}}{\sum_k \exp \frac{\Pi_{s0}(\mathcal{S}_0, \varsigma, \theta_2, \theta_3, \sigma, f_{s1})}{\sigma}} \tag{20}$$

With these probabilities, as functions of the payoff parameters, in hand the second stage can be estimated in various ways.[21,22] One method is to estimate the parameters $(\theta_2, \theta_3, \sigma)$ using observed station choices by applying a standard multinomial logit maximum likelihood estimator. As I discuss below there a good reasons to believe that this estimator may perform poorly in practice, given the possibility that the estimated station payoffs from making different choices contain small amounts of error, resulting either from simulation error or from a failure of the model to account correctly for the opportunities facing an individual station even though it seems to do a good job on average. In particular this tends to result in an overestimation of the variance of the switching cost distribution. I therefore also consider an alternative method of moments estimator which exploits differences in how good opportunities in different formats appear to AM and FM stations which produces much more plausible estimates of the variance of the switching cost distribution.

6 Results

This section reports the results of estimating demand using a sample of 40 markets listed in Table 5. These markets were a random sample chosen from the set of markets with a limited presence of out of market stations. This selection rule means that there are no markets from the densely populated north east where cross market listening is common, but the estimation sample does include a range of markets of different sizes with varying ethnic/racial demographics.

[21] The calculation of expected future εs exploits the fact that the conditional expectation of the ε of the chosen choice is simply a function of σ, Euler's constant and the probability of that choice being made. This is the primary motivation for assuming a Type I extreme value distribution for the εs rather than, for example, a high-dimensional truncated multivariate normal.

[22] The forward simulations only need to be performed once when (19) is linear in the payoff parameters (Hotz et al. (1994) and BBL).

6.1 First Stage: Listener Demand

Tables 6(a) and (b) present the estimated coefficients from random coefficients logit model of listener demand.[23] The missing parameters in the Table 6(b) correspond to formats where no stations are observed. For the rest of the analysis it is assumed that it is not possible for stations to choose these formats.

The demographic taste parameters show the expected pattern and most of them are precisely estimated. Relative to the excluded group of white men aged 12-24, older listeners dislike Contemporary Hit Radio/Top 40 and prefer News/Talk, Rock and Religious programming. Female listeners like Adult Contemporary and Religious programming and dislike News/Talk radio. Blacks like Urban and Religious programming and dislike News/Talk, Country and Rock.

The standard deviation parameters for the random coefficients on format tastes are mostly small and insignificantly different from zero. This indicates that demographics capture the most important differences in how different formats (rather than stations) appeal to individuals within markets (market-format fixed effects capture the possibility that tastes for formats such as Country vary geographically). The level of the market-format fixed effects in Table 6(b) should be interpreted in conjunction with these standard deviations. For example, because Adult Contemporary has a higher standard deviation than other music formats, Adult Contemporary stations can still get similar listenership even though the coefficients on the Adult Contemporary fixed effects are systematically lower.[24]

The station characteristic coefficients indicate that stations with more coverage and more powerful transmitters are of higher quality. The relatively small number of out of market stations in the sample

[23] The parameters which are not listed include a set of time dummies. The time coefficients are all small and statistically insignificant (this reflects the fact that I take out the trend in radio listenership when calculating the share data). When I simulate forward I ignore their effects.

[24] The standard deviation on the constant for commercial radio listening is also small. This happens partly because market-format fixed effects are included. In the absence of these effects, this parameter tends to be much larger in order to rationalize the pattern that even with more Arbitron-rated stations in larger markets total radio listening increases only slightly. with market-format fixed effects this pattern can be explained by slightly lower market-format fixed effects in larger markets. A possible robustness check on the results would be to see if the results are changed significantly if this parameter is fixed at a higher value.

are estimated to be of lower quality. The coefficient on the dummy for stations which are sometimes too small to be rated by Arbitron is negative, as expected, and highly significant. While one might argue that it is somewhat arbitrary to include this variable, it is useful in reducing the variance of the unobserved quality characteristic. The age and FM height variables have the wrong signs and are statistically insignificant: if the coverage and power variables are excluded, the sign on these variables changes and they become statistically significant.

As explained above, the format x band interaction coefficients play a potentially important role in identifying switching costs. FM stations are estimated to have higher average quality for all formats, but as expected the difference between AM and FM is smallest for News/Talk and highest for Contemporary Hit Radio and Rock. The relatively small coefficient on the Adult Contemporary interaction is less attractive as there are relatively few AM stations in that format.

The bottom part of the table shows the estimates of the parameters governing the evolution of unobserved station quality. The estimated serial correlation parameter ρ is 0.834 (0.007). The estimated standard deviations of the innovations of station quality show that switchers receive slightly more volatile quality shocks, but the difference is not large, consistent with the relatively small variance of changes to station shares. The estimate of μ_2^ξ suggests that the unobserved quality of switching stations tends to increase by a small and barely significant amount on average.

As the demand parameters are an input into the rest of the analysis it is important to see how well the combination of the data and the model fit my structural assumptions and how the model performs at predicting changes in station shares.

I assume that the innovations in station quality are drawn from normal distributions. Figure 3 shows the kernel density estimates of these innovations for switching and non-switching stations. Both densities are close to normal, with slightly more weight in the tails than would be expected given a normal distribution. Figure 3 also shows a kernel density estimate for unobserved station quality (ξ). This density is also close to a normal with slightly too much weight in the lower tail (i.e., there are more stations with small shares than a normal distribution would predict).

Figure 4 compares the predicted and actual changes in share for switching and non-switching stations when the demand is model is simulated one period forward (i.e., stations make the format switches actually seen in the data but random draws are made for the innovations in station quality). Table 7 compares the means and standard deviations of these changes and also calculates the correlation between the actual and simulated changes for individual station-quarter observations. The match in the distributions for switching stations is very good: the standard deviation for the simulations is higher because of a few extreme increases in share in the upper tail. However, when averages are taken across multiple simulations this upper tail disappears, so that all of the averages are within the range seen in the actual data. The correlation in changes for individual stations is also impressively high (0.51) when averages are used. Surprisingly the fit of the overall distribution is less good for the stations which do not switch formats, with the simulated model predicting small decreases in shares. The correlation in changes is also poorer, but this is not surprising as when stations do not change format there is less of a "structural change" which the model can match.

6.2 First Stage: Station Conditional Choice Probabilities

Table 8 presents a selection of the parameters from the multinomial logit model used to estimate station conditional choice probabilities. The model also includes a full set of market dummies interacted with a dummy for whether the chosen format requires a format switch. These interactions allow the average switching probability to differ across markets, which, as explained above, can help to identify the composition of format switching costs. The variables for the Dark format are all set equal to zero.

While these coefficients should not be interpreted structurally, there are some sensible patterns, even though most of the coefficients are not statistically significant (partly because of the large number of included variables). As expected FM stations are significantly more likely than AM stations to enter contemporary music formats such as Rock and Country, and significantly less likely to enter News/Talk. A larger Hispanic population reduces the probability of entry into most formats other than Spanish while a higher Black population increases the probability of entry into Urban and Religious programming.[25] Higher market-format quality (relative to the format average) tends to increase the probability of that format being chosen, while more competing stations and competing stations with larger shares (shares are a function of the state space parameters including the "unobserved" station qualities) tends to reduce entry. The "other variables" coefficients show that stations with larger shares and higher "unobserved" qualities are less likely to switch formats, and in particular stations with higher shares are much less likely to switch to the Dark (inactive) format. The final coefficient indicates that stations which have switched in the last year, are slightly, but not significantly, more likely to make another switch.

6.3 Second Stage Estimates

[to be presented at seminar].

7 Conclusion

This paper presents some preliminary estimates of product repositioning costs in the radio industry. These costs play an important role in the analysis of horizontal mergers and will affect how quickly the set of available products responds to demand and supply shocks. I use a dynamic model to estimate these costs, using assumptions on the timing of format choices and innovations in unobserved station quality to address the problem of estimating demand when product characteristics are endogenous. These assumptions are similar to those used in the literature on estimating production functions.

[25] I have also estimated the conditional choice probabilities included age x sex demographics. None of these variables was statistically significant and they did not show an intuitive pattern, probably because of limited variation in these demographics across markets (or over time).

References

[1] Ackerberg, Daniel A., C. Lanier Benkard, Steven Berry and Ariel Pakes, "Econometric Tools for Analyzing Market Outcomes", mimeo, Stanford University

[2] Ackerberg, Daniel A., Kevin Caves and Garth Frazer (2005), "Structural Identification of Production Functions", mimeo, UCLA

[3] Aguirregabiria, Victor and Pedro Mira (2006), "Sequential Estimation of Dynamic Discrete Games", forthcoming *Econometrica*

[4] Anderson, Simon P. and Stephen Coate (2005), "Market Provision of Broadcasting: A Welfare Analysis", *Review of Economic Studies*, 72(4), 947-972

[5] Arbitron Company (2002), *Arbitron Radio Market Report Reference Guide*, New York, NY: Arbitron Company

[6] Bajari, Patrick, Lanier Benkard and Jonathan Levin (2006), "Estimating Dynamic Models of Imperfect Competition", forthcoming *Econometrica*

[7] Beresteanu, Arie and Paul B. Ellickson (2006), "The Dynamics of Retail Oligopoly", mimeo, Duke University

[8] Berger, Allen N., Seth D. Bonime, Lawrence G. Goldberg and Lawrence J. White (2004), "The Dynamics of Market Entry: The Effects of Mergers and Acquisitions on Entry in the Banking Industry", *Journal of Business*, 77(4), 797-834

[9] Berry, Steven T. (1994), "Estimating Discrete-Choice Models of Product Differentiation", *RAND Journal of Economics*, 25(2), 242-262

[10] Berry, Steven T., James Levinsohn and Ariel Pakes (1995), "Automobile Prices in Market Equilibrium", *Econometrica*, 63, 841-890

[11] Berry, Steven T. and Joel Waldfogel (1999a), "Free Entry and Social Inefficiency in Radio Broadcasting", *RAND Journal of Economics*, 30(2), 397-420

[12] Berry, Steven T. and Joel Waldfogel (1999b), "Mergers, Station Entry and Programming Variety in Radio Broadcasting", National Bureau of Economic Research Working Paper No. 7080

[13] Berry, Steven T. and Joel Waldfogel (1999c), "Public Radio in the United States: Does it Correct Market Failure or Cannibalize Commercial Stations?", *Journal of Public Economics*, 71(2), 189-211

[14] Berry, Steven T. and Joel Waldfogel (2001), "Do Mergers Increase Product Variety? Evidence from Radio Broadcasting", *Quarterly Journal of Economics*, 116(3), 1009-1025

[15] BIA Financial Network, Inc. (2001), *Media Access Pro User's Manual, version 3.0*, Chantilly, VA: BIA Financial Network, Inc.

[16] Blundell, Richard and Stephen Bond (2000), "GMM Estimation with Persistent Panel Data: An Application to Production Functions", *Econometric Reviews*, 19, 321-340

[17] Borenstein, Severin (1986), "Too Much Rock and Roll?: Business Stealing Effects in Radio Station Format Choice", mimeo, University of Michigan

[18] Borenstein, Severin and Janet S. Netz (1999), "Why Do All the Flights Leave at 8 am? Competition and Departure-Time Differentiation in Airline Markets", *International Journal of Industrial Organization*, 17(5), 611-640

[19] Bresnahan, Timothy and Peter Reiss (1991), "Entry and Competition in Concentrated Markets", *Journal of Political Economy*, 99(5), 977-1009

[20] Brown, Keith and George Williams (2002), "Consolidation and Advertising Prices in Local Radio Markets", mimeo, Federal Communications Commission

[21] Chambers, Todd (2003), "Radio Programming Diversity in the Era of Consolidation", *Journal of Radio Studies*, 10(1), 33-45

[22] Collard-Wexler, Allan (2005), "Plant Turnover and Demand Fluctuations in the Ready-Mix Concrete Industry", mimeo, Northwestern University

[23] Crawford, Gregory S. and Matthew Shum (2006), "The Welfare Effects of Endgenous Quality Choice: The Case of Cable Television", mimeo, University of Arizona

[24] Cunningham, Brendan M. and Peter J. Alexander (2004), "A Theory of Broadcast Media Competition and Advertising", *Journal of Public Economic Theory*, 6(4), 537-636

[25] DiCola, Peter and Kristin Thomson (2002), *Radio Deregulation: Has It Served Citizens and Musicians?*, Washington DC: Future of Music Coalition

[26] Draganaska, Michaela, Michael Mazzeo and Katja Seim (2006), "Modeling Joint Pricing and Product Assortment Choices", mimeo, Stanford University

[27] Doraszelski, Uli and Mark Satterthwaite (2003), "Foundations of Markov Perfect Industry Dynamics: Existence, Purification and Multiplicity", mimeo, Northwestern University

[28] European Commission (1997), *Commission Notice on the Definition of the Relevant Market for the Purposes of Community Competition Law*, Official Juournal 372, December 9, 1997

[29] Ericson, Richard and Ariel Pakes, "Markov Perfect Industry Dynamics: A Framework for Empirical Work", *Review of Economic Studies*, 62, 53-82

[30] Federal Communications Commission (2001), *Review of the Radio Industry, 2001*, Mass Media Bureau Policy and Rules Division, Washington DC: Federal Communications Commission

[31] Gabszewicz, Jean J., Didier Laussel and Nathalie Sonnac (2001), "TV-Broadcasting Competition and Advertising", mimeo, Université Catholique de Louvain

[32] Gandhi, Amit, Luke Froeb, Steven Tschantz and Gregory J. Werden (2005), "Post-Merger Product Repositioning", *mimeo*, Vanderbilt University

[33] Greene, William H. (1997), *Econometric Analysis*, 3^{rd} Edition, Upper Saddle River, NJ: Prentice Hall

[34] Hausman, Jerry A., Bronwyn H. Hall and Zvi Griliches (1984), "Econometric Models for Count Data with an Application to the Patents-R & D Relationship", *Econometrica*, 52(4), 909-938

[35] Hitsch, Gunter J. (2006), "An Empirical Model of Optimal Dynamic Product Launch and Exit Under Demand Uncertainty", *Marketing Science*, 25(1), 25-50

[36] Hotz, V. Joseph and Robert A. Miller (1993), "Conditional Choice Probabilities and the Estimation of Dynamic Models", *Review of Economic Studies*, 60(3), 497-529

[37] Hotz, V. Joseph, Robert A. Miller, Seth Sanders and Jeffrey Smith (1994), "A Simulation Estimator for Dynamic Models of Discrete Choice", *Review of Economic Studies*, 61(2), 265-89

[38] Kennan, John and James R. Walker (2005), "The Effect of Expected Income on Individual Migration Decisions", mimeo, University of Wisconsin-Madison

[39] Klein, Joel I. (1997), "DOJ Analysis of Radio Mergers", speech delivered in Washington, DC , February 19, 1997, http://www.usdoj.gov/atr/public/speeches/1055.pdf

[40] Judd, Kenneth (1985), "Credible Spatial Preemption", 16(1), *RAND Journal of Economics*

[41] Levinsohn, James and Amil Petrin (2003), "Estimating Production Functions Using Inputs to Control for Unobservables", *Review of Economic Studies*

[42] Macieira, Joao (2006), "Measuing the Effects of Innovation Subsidies: The Case of Supercomputers", mimeo, Northwestern University

[43] Mankiw, N. Gregory and Michael D. Whinston (1986), "Free Entry and Social Efficiency", *RAND Journal of Economics*, 17(1), 48-58

[44] M Street Journal, *STAR Ratings* (www.stationratings.com), Littleton, NH: M Street Journal

[45] National Association of Broadcasters (2002), "Future of Music Coalition Circulates Flawed Study Containing Inaccurate Conclusions About the Radio Industry", press release, 15 November 2002, Washington DC: National Association of Broadcasters

[46] Nevo, Aviv (2000), "A Practioner's Guide to Estimation of Random-Coefficients Logit Models of Demand", *Journal of Economics and Management Strategy*, 9(4), 513-548

[47] Olley, Steven and Ariel Pakes (1996), "The Dynamics of Productivity in the Telecommunications Industry", *Econometrica*, 64, 1263-1295

[48] Pakes, Ariel, Michael Ostrovsky and Steven T. Berry (2005), "Simple Estimators for the Parameters of Discrete Dynamic Games (with Entry/Exit Examples)", mimeo, Harvard University

[49] Pesendorfer, Martin and Phillip Schmidt-Dengler (2003), "Identification and Estimation of Dynamic Games", CEPR Discussion Paper 3965

[50] Peters, Craig (2006), "Evaluating the Performance of Merger Simulation: Evidence from the US Airline Industry", *Journal of Law and Economics*, XLIX, 627-649

[51] Petrin, Amil (2002), "Quantifying the Benefits of New Products: The Case of the Minivan", *Journal of Political Economy*, 110(4), 705-729

[52] Radio Advertising Bureau (2004), *Radio Marketing Guide & Fact Book for Advertisers*, New York: Radio Advertising Bureau, www.rab.com

[53] Romeo, Charles and Andrew Dick (2005), "The Effect of Format Changes and Ownership Consolidation on Radio Station Outcomes", mimeo, US Department of Justice

[54] Rogers, Robert P. and John R. Woodbury (1996), "Market Structure, Program Diversity and Radio Audience Size", *Contemporary Economic Policy*, XIV(1), 81-91

[55] Rust, John (1987), "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher", *Econometrica*, 55(5), 999-1033

[56] Ryan, Stephen P. (2005), "The Costs of Environmental Regulation in a Concentrated Industry", mimeo, MIT

[57] Ryan, Stephen P. and Catherine Tucker (2006), "Heterogeneity and the Dynamics of Technology Adoption", mimeo, MIT

[58] Sweeting, Andrew T. (2006), "Too Much Rock and Roll? Station Ownership, Programming and Listenership in the Music Radio Industry", mimeo, Northwestern University

[59] Tirole, Jean M. (1988), *The Theory of Industrial Organization*, Cambridge, MA: MIT Press

[60] Tyler Mooney, Catherine (2006), "The Determinants and Effects of Market Structure in the Radio Broadcasting Industry", mimeo, University of Virginia

[61] United States Department of Justice and Federal Trade Commission (1997), *Horizontal Merger Guidelines*, Washington DC: Department of Justice

[62] United States Department of Justice (1999), "Justice Department Approves Clear Channel's Acquisition of Jacor Communications after Parties Agree to Divestitures", press release, April 22 1999

[63] United States Department of Justice (2000a), "Justice Department Requires Divestitures in Kansas City Radio Acquisition", press release, July 14 2000

[64] United States Department of Justice (2000b), "Justice Department Requires Clear Channel and AMFM to Divest 99 Radio Stations in 27 Markets", press release, July 20 2000

[65] United States Department of Justice (2000c), "United States v. Clear Channel Communications, Inc. and AMFM Inc.: Competitive Impact Statement", November 15, 2000

[66] Williams, George and Scott Roberts (2002), "Radio Industry Review 2002: Trends in Ownership, Format, and Finance", Media Bureau Staff Research Paper, Washington DC: Federal Communications Commission

Table 1: Formats and Demographics

My Formats	Contains BIAfn Format Categories	Band % AM	Average Format Demographics % Female	% Under 25	% Under 49	% Black	% Hispanic
AC	Adult Contemporary	6.2%	63.7%	13.9%	70.6%	7%	12%
CHR	Contemporary Hit Radio/Top 40	1.4%	61.0%	47.1%	92.7%	21%	24%
Country	Country	19.8%	53.2%	15.7%	61.3%	2%	6%
Oldies	Oldies	22.8%	51.4%	8.2%	45.8%	6%	15%
Rock	Album Oriented Rock /Classic Rock Rock	1.7%	32.3%	23.1%	84.2%	3%	10%
Urban	Urban	21.8%	54.6%	33.3%	80.0%	81%	6%
News/Talk	News, Talk, Sports	91.6%	34.6%	3.3%	44.0%	8%	6%
Other Music	Classical, Jazz, Easy Listening Middle of the Road, Nostalgia/Big Band Miscellaneous, Ethnic	64.6%	54.4%	7.9%	44.6%	20%	7%
Religion	Religion	71.2%	65.5%	7.8%	57.6%	34%	9%
Spanish Language	Spanish	56.0%	48.4%	25.3%	81.1%	1%	96%

Notes: Female and age data calculated based on Arbitron data for Spring 2006. Black, hispanic data based on Arbitron estimates for Spring 2004 reported in 2005 *Radio Today* report. These are based on a sample of markets where Aribtron tracks ethnic/racial listening. Band proportions calculated using data from Spring 1997 to Spring 2006.

Table 2: Format Switching Patterns

FM Stations

From	Number stations-qtrs	Relative share	Number switching out	Number switching in	Proport. switching out	Proportion of stations switching out, switching to: Dark	AC	CHR	Cntry	Old	Rock	Urban	News	OtherM	Relig	Span
Dark	1,102	N/A	195	32	0.18		0.13	0.07	0.14	0.09	0.22	0.07	0.06	0.10	0.08	0.06
Adult Contemporary	9,005	1.03	377	424	0.04	0.01		0.24	0.10	0.13	0.24	0.06	0.05	0.07	0.02	0.07
Contemporary Hit Radio/Top 40	4,867	1.25	241	310	0.05	0.00	0.26		0.07	0.05	0.20	0.25	0.02	0.04	0.05	0.05
Country	7,791	1.23	287	192	0.04	0.02	0.17	0.12		0.10	0.21	0.08	0.07	0.09	0.04	0.09
Oldies	4,139	0.90	284	194	0.07	0.01	0.29	0.08	0.11		0.26	0.10	0.04	0.04	0.02	0.05
Rock	10,445	0.92	337	396	0.03	0.01	0.28	0.14	0.08	0.11		0.09	0.08	0.07	0.05	0.09
Urban	3,770	1.24	143	222	0.04		0.17	0.30	0.08	0.11	0.11		0.04	0.04	0.08	0.06
News/Talk/Sports	1,153	0.59	63	118	0.05	0.03	0.08	0.10	0.11	0.08	0.25	0.03		0.11	0.08	0.13
Other Music	2,811	0.82	221	148	0.08	0.02	0.26	0.13	0.12	0.06	0.17	0.09	0.04		0.04	0.07
Religion	2,488	0.42	94	102	0.04	0.04	0.17	0.06	0.05	0.12	0.14	0.12	0.06	0.10		0.14
Spanish-language	2,789	0.71	62	166	0.02	0.06	0.11	0.29	0.06	0.03	0.05	0.15	0.03	0.13	0.08	

AM Stations

From	Number stations-qtrs	Relative share	Number switching out	Number switching in	Proport. switching out	Proportion of stations switching out, switching to: Dark	AC	CHR	Cntry	Old	Rock	Urban	News	OtherM	Relig	Span
Dark	396	N/A	108	54	0.27		0.03	0	0.09	0.06	0.03	0.03	0.30	0.17	0.20	0.09
Adult Contemporary	600	0.77	66	36	0.11	0.03		0	0.11	0.15	0.02	0	0.26	0.35	0.02	0.08
Contemporary Hit Radio/Top 40	62	1.07	15	12	0.24	0.07	0		0	0.07	0.07	0	0.27	0.27	0.07	0.20
Country	1,897	0.70	150	111	0.08	0.02	0.01	0		0.07	0.03	0.01	0.42	0.23	0.13	0.07
Oldies	1,185	0.68	111	123	0.09	0.02	0.04	0.01	0.12		0.02	0.02	0.44	0.16	0.14	0.05
Rock	180	0.61	48	30	0.27	0.04	0	0.06	0.06	0.10		0.06	0.29	0.15	0.19	0.04
Urban	1,064	0.82	74	43	0.07	0.05	0.01	0	0.01	0.05	0		0.32	0.18	0.26	0.11
News/Talk/Sports	12,796	1.26	317	482	0.02	0.06	0.02	0.01	0.13	0.09	0.02	0.02		0.26	0.17	0.22
Other Music	5,001	1.02	313	253	0.06	0.03	0.05	0.01	0.07	0.14	0.03	0.01	0.47		0.08	0.11
Religion	6,022	0.63	171	183	0.03	0.06	0.01	0.01	0.06	0.03	0.01	0.11	0.40	0.13		0.17
Spanish-language	3,573	0.64	131	177	0.04	0.03	0.02	0	0.03	0.05	0.01	0.02	0.49	0.23	0.11	

Note: numbers calculated using data on home market stations from Spring 1997 to Spring 2006 from 197 markets described in Section 2. The "relative share" of a station is calculated using all station-quarters with enough listeners to be rated by Arbitron. For each market-quarter I calculate the mean share of rated stations in each band, and calculate each station's relative share by dividing its share by this market-quarter-band-specific mean. The number reported is the mean of this relative share across all stations in a category.

Table 3: Comparison of Listening Shares and Changes in Shares for Switchers and Non-Switchers

	Average share quarter 1	Average share quarter 2	Change qtr 1 to qtr 2	Average share quarter 3	Change qtr 2 to quarter 3	Average Arbitron Market Rank
Non-switchers	4.04 (3.11)	4.02 (3.07)	-0.03 (1.11)***	3.98 (3.04)	-0.03 (1.10)***	84.2 (57.6)
Switchers	2.65 (2.22)	2.87 (2.27)	0.22 (1.43)***	3.00 (2.32)	0.13 (1.10)***	86.6 (55.6)
Difference between switchers and non-switchers	-1.40***	-1.15***	0.24***	-0.98***	0.17***	2.3

Note: share is measured as a % of radio listening. Stations used are active (not Dark), home market stations rated by Arbitron in three successive quarters. A switcher is a station changing format between quarter 1 and quarter 2 and not changing formats between quarter 2 and quarter 3. Non-switchers are stations not changing format between quarters 1 and 3. *** indicates differences or changes which are significantly different from zero at the 1% level. Standard deviations in parentheses.

Table 4: Proportion of Home Market Stations in A Market-Category

(a) Between Market Regressions

	AC	CHR	Cntry	Oldies	Rock	Urban	News	Other M	Relig	Spanish
East South Central	-0.025	0.001	0.061	0.005	-0.032	-0.019	0.010	-0.045	0.050	0.004
	(0.019)	(0.011)	(0.016)***	(0.015)	(0.020)	(0.011)*	(0.023)	(0.020)**	(0.019)***	(0.017)
Mid Atlantic	0.006	0.017	-0.027	0.025	0.006	-0.012	-0.015	0.032	-0.004	-0.009
	(0.016)	(0.010)*	(0.013)**	(0.013)**	(0.016)	(0.009)	(0.019)	(0.016)**	(0.016)	(0.014)
Mountain	0.005	0.003	-0.028	0.002	-0.023	-0.017	0.010	0.011	0.004	0.008
	(0.022)	(0.013)	(0.019)	(0.017)	(0.023)	(0.013)	(0.026)	(0.023)	(0.022)	(0.019)
New England	0.019	0.012	-0.063	0.005	0.020	-0.002	0.020	0.040	-0.040	0.028
	(0.019)	(0.011)	(0.016)***	(0.014)	(0.020)	(0.011)	(0.022)	(0.019)**	(0.018)**	(0.016)*
Pacific	0.007	0.005	-0.042	-0.015	-0.037	-0.010	-0.007	0.021	0.025	0.043
	(0.019)	(0.011)	(0.017)**	(0.015)	(0.019)*	(0.011)	(0.022)	(0.020)	(0.019)	(0.017)**
South Atlantic	-0.026	0.002	0.022	-0.004	-0.030	-0.018	0.026	-0.015	0.032	0.010
	(0.016)	(0.010)	(0.014)	(0.013)	(0.017)*	(0.009)*	(0.019)	(0.017)	(0.016)**	(0.014)
West North Central	-0.005	0.010	0.018	0.000	0.012	-0.026	0.012	-0.006	-0.015	-0.009
	(0.020)	(0.012)	(0.018)	(0.016)	(0.021)	(0.011)**	(0.024)	(0.021)	(0.020)	(0.017)
West South Central	-0.034	0.003	0.061	0.006	-0.034	-0.014	0.000	-0.030	0.020	0.015
	(0.018)*	(0.011)	(0.016)***	(0.014)	(0.018)*	(0.010)	(0.021)	(0.019)	(0.018)	(0.016)
Proportion Black	-0.059	-0.048	-0.262	0.041	-0.132	0.486	-0.140	-0.021	0.144	-0.016
	(0.065)	(0.039)	(0.057)***	(0.052)	(0.067)*	(0.038)***	(0.077)*	(0.068)	(0.066)**	(0.058)
Proportion Hispanic	-0.107	-0.020	-0.164	-0.011	-0.063	-0.014	-0.140	0.011	-0.135	0.637
	(0.042)**	(0.026)	(0.037)***	(0.034)	(0.044)	(0.024)	(0.051)***	(0.045)	(0.043)***	(0.042)***
Proportion Female	-0.423	-0.310	-1.214	-1.356	-0.959	0.515	0.277	0.219	2.348	0.648
	(0.638)	(0.392)	(0.562)**	(0.509)***	(0.666)	(0.367)	(0.765)	(0.664)	(0.635)***	(0.562)
Proportion 12-24	-0.190	0.368	1.249	0.277	-0.118	0.156	-0.724	-0.924	-0.005	-0.337
	(0.376)	(0.229)	(0.327)***	(0.304)	(0.394)	(0.216)	(0.460)	(0.397)**	(0.384)	(0.333)
Proportion 25-34	-0.994	0.131	0.368	-0.774	-0.797	0.778	-0.292	-0.105	0.677	0.845
	(0.668)	(0.406)	(0.581)	(0.541)	(0.704)	(0.384)**	(0.818)	(0.702)	(0.675)	(0.591)
Proportion 50-64	-0.432	0.197	1.945	0.625	0.186	0.335	-2.419	-0.628	0.067	-0.416
	(0.814)	(0.502)	(0.714)***	(0.660)	(0.858)	(0.469)	(0.979)**	(0.861)	(0.828)	(0.723)
Proportion 65plus	-0.322	0.215	0.293	-0.001	-0.542	0.316	0.289	-0.075	-0.342	0.134
	(0.331)	(0.202)	(0.291)	(0.266)	(0.346)	(0.191)*	(0.403)	(0.349)	(0.336)	(0.293)
Out of Market Share	-0.233	-0.201	-0.027	0.190	-0.286	-0.338	0.052	0.377	-0.123	0.038
	(0.132)*	(0.110)*	(0.169)	(0.249)	(0.124)**	(0.117)***	(0.141)	(0.249)	(1.520)	(0.354)
Number of markets	197	197	197	197	197	197	197	197	197	197

Notes: dependent variable is the proportion of home market stations in a market category. "Out of Market Share" is instrumented for using the predicted share of out of market stations based on the out of market stations' shares in their home markets and the average proportion of listening to stations in those markets across categories and quarters.

Table 4: Proportion of Home Market Stations in A Market-Category

(b) Within Market Regressions

	AC	CHR	Cntry	Oldies	Rock	Urban	News	Other M	Relig	Spanish
Proportion Black	0.005	-0.393	-0.144	-0.928	0.057	0.709	-0.712	0.379	0.906	-0.202
	(0.218)	(0.160)**	(0.201)	(0.233)***	(0.203)	(0.148)***	(0.246)***	(0.261)	(0.192)***	(0.160)
Proportion Hispanic	0.294	0.220	-0.039	0.080	-0.350	0.047	-0.580	-0.038	-0.397	1.016
	(0.087)***	(0.064)***	(0.080)	(0.093)	(0.081)***	(0.059)	(0.100)***	(0.109)	(0.077)***	(0.068)***
Out of Market Share	-0.057	-0.007	-0.876	-1.249	-0.419	-0.304	-0.346	1.043	-2.373	-0.214
	(0.109)	(0.066)	(0.229)***	(0.147)***	(0.097)***	(0.068)***	(0.218)	(0.220)***	(0.302)***	(0.155)
Number of market-quarters	3,710	3,710	3,710	3,710	3,710	3,710	3,710	3,710	3,710	3,710

Notes: dependent variable is the proportion of home market stations in a market category. "Out of Market Share" is instrumented for using the predicted share of out of market stations based on the out of market stations' shares in their home markets and the average proportion of listening to stations in those markets across categories and quarters. A full set of quarter dummies are also included.

Table 5 : Markets Used in Estimating the Structural Model

		Proportion Black		Proportion Hispanic		Proportion	Revenue ($) Per
Market Name	Population (M)	Min	Max	Min.	Max.	Outside Listening	Listener Year
Chicago, IL	7.41	0.18	0.18	0.14	0.18	0.00	488.11
Dallas - Ft. Worth	4.24	0.13	0.14	0.18	0.24	0.00	602.85
Houston-Galveston	3.84	0.16	0.17	0.25	0.31	0.01	558.88
Atlanta, GA	3.39	0.27	0.31	0.05	0.08	0.00	771.77
Miami-Ft. Lauderdale-Hollywood	3.29	0.18	0.20	0.39	0.45	0.02	528.66
Seattle-Tacoma	3.01	0.04	0.05	0.04	0.06	0.00	587.72
Phoenix, AZ	2.49	0.03	0.04	0.20	0.26	0.01	615.11
Minneapolis - St. Paul	2.47	0.05	0.06	0.03	0.04	0.00	481.57
St. Louis	2.16	0.17	0.18	0.01	0.02	0.00	472.24
Tampa-St. Petersburg-Clearwater	2.04	0.09	0.10	0.09	0.13	0.01	469.64
Denver - Boulder	2.02	0.05	0.05	0.15	0.19	0.00	666.25
Kansas City	1.46	0.12	0.12	0.04	0.06	0.01	502.95
Salt Lake City - Ogden	1.35	0.01	0.01	0.08	0.11	0.00	507.44
Columbus, OH	1.32	0.13	0.14	0.01	0.02	0.01	555.41
Indianapolis, IN	1.21	0.14	0.14	0.02	0.04	0.01	584.54
Las Vegas, NV	1.17	0.09	0.09	0.18	0.24	0.00	553.61
Memphis	0.99	0.41	0.43	0.02	0.03	0.01	346.84
Jacksonville, FL	0.95	0.20	0.21	0.03	0.05	0.00	483.46
Honolulu	0.75	0.02	0.03	0.04	0.06	0.00	363.01
Tulsa, OK	0.69	0.08	0.08	0.04	0.06	0.00	469.66
Albuquerque, NM	0.59	0.02	0.02	0.38	0.41	0.01	487.90
Spokane, WA	0.44	0.01	0.01	0.02	0.03	0.00	372.76
Boise, ID	0.35	0.00	0.01	0.07	0.09	0.00	491.46
Jackson, MS	0.36	0.43	0.46	0.01	0.01	0.00	418.76
Reno, NV	0.33	0.02	0.02	0.13	0.18	0.00	548.53
Montgomery, AL	0.27	0.37	0.40	0.01	0.01	0.04	460.77
Tallahassee, FL	0.23	0.26	0.27	0.03	0.04	0.04	499.93
Anchorage, AK	0.22	0.05	0.06	0.05	0.06	0.01	653.17
Columbus, GA	0.21	0.40	0.43	0.04	0.04	0.04	483.80
Lubbock, TX	0.20	0.07	0.07	0.24	0.27	0.00	441.18
Odessa - Midland, TX	0.19	0.05	0.06	0.31	0.39	0.00	308.36
Amarillo, TX	0.18	0.06	0.06	0.16	0.21	0.01	353.69
Abilene, TX	0.13	0.06	0.07	0.15	0.18	0.02	367.55
Monroe, LA	0.12	0.31	0.33	0.01	0.01	0.02	698.39
Billings, MT	0.11	0.00	0.00	0.03	0.04	0.00	480.00
Albany, GA	0.10	0.48	0.51	0.01	0.01	0.02	429.58
San Angelo, TX	0.09	0.04	0.04	0.27	0.32	0.00	394.59
Bismarck, ND	0.08	0.00	0.00	0.01	0.01	0.00	575.42
Meridian, MS	0.06	0.35	0.39	0.01	0.01	0.01	727.82
Casper, WY	0.06	0.01	0.01	0.04	0.05	0.00	481.69

Note: population estimates and demographics from County population estimates of the US Census. Proportion outside listening is average proportion of rated radio listening to stations which were not home to the market 1997-2006. Revenue per listener year is BIAfn estimated market revenues for 2006 divided by number of listener-years in market

Table 6: Listener Demand Model

Demographic Effects and Random Coefficients

	Age 25-49		Age 50 +		Female	
Adult Contemporary	0.567	(0.102)	0.036	(0.148)	0.676	(0.104)
Contemporary Hit Radio/Top 40	-0.741	(0.109)	-2.037	(0.251)	0.504	(0.061)
Country	0.498	(0.087)	0.625	(0.130)	-0.013	(0.052)
Oldies	1.322	(0.379)	1.954	(0.395)	-0.187	(0.062)
Rock	0.409	(0.085)	-0.635	(0.119)	-0.787	(0.052)
Urban	-0.186	(0.119)	-0.493	(0.197)	-0.017	(0.040)
News	5.088	(4.221)	5.472	(4.224)	-1.020	(0.130)
Other Music	2.064	(0.862)	3.092	(0.919)	0.065	(0.061)
Religious	3.018	(2.210)	3.522	(2.244)	0.462	(0.103)
Spanish	0.140	(0.097)	0.171	(0.162)	0.025	(0.067)

	Black		Hispanic		Std Deviations of RC	
Adult Contemporary	-0.768	(0.109)	-0.330	(0.121)	1.953	(0.651)
Contemporary Hit Radio/Top 40	0.500	(0.101)	0.419	(0.122)	0.842	(1.405)
Country	-1.940	(0.087)	-1.360	(0.093)	0.000	(2.619)
Oldies	-0.911	(0.107)	-0.247	(0.152)	0.615	(1.388)
Rock	-1.932	(0.070)	-0.944	(0.076)	0.000	(0.757)
Urban	3.476	(0.087)	0.468	(0.073)	0.001	(1.122)
News	-0.885	(0.128)	-1.532	(0.158)	2.155	(0.545)
Other Music	0.219	(0.089)	-1.066	(0.130)	0.107	(1.112)
Religious	1.429	(0.144)	-0.267	(0.152)	1.512	(0.643)
Spanish	-0.784	(0.071)	4.334	(0.070)	0.116	(0.798)
Constant (commercial radio)					0.958	(0.379)

Station Quality Parameters

	FM *	
Adult Contemporary	0.800	(0.367)
Contemporary Hit Radio/Top 40	1.848	(0.533)
Country	0.895	(0.281)
Oldies	0.997	(0.324)
Rock	1.425	(0.345)
Urban	1.463	(0.270)
News	0.669	(0.300)
Other Music	0.970	(0.262)
Religious	1.124	(0.263)
Spanish	1.281	(0.282)
Signal coverage	1.111	(0.243)
FM*signal coverage	-0.124	(0.254)
Unlisted station	-0.887	(0.077)
Out of market station	-0.195	(0.178)
Signal power FM	14.425	(8.550)
Signal power AM	12.801	(2.793)
Transmitter height FM	-8.399	(45.646)
Station Age	-18.187	(89.570)

Evolution of Station Quality

ρ^{ξ}	0.834	(0.007)
Mean change switchers	0.050	(0.029)
Standard deviation of innovation switchers	0.559	(0.018)
Standard deviation of innovation non-switchers	0.4117	(0.002)
Observations	15,493	
GMM Objective	909.1	DoF:422

Notes: robust standard errors in parentheses

Table 6 cont.: Market-Format Coefficient Estimates from Listener Demand Model
(Missing market-formats have no observed dtations)

	AC	CHR	Country	Oldies	Rock	Urban	News/Talk	Other M	Religion	Spanish
Chicago, IL	-8.818	-7.464	-7.121	-8.659	-7.054	-9.001	-13.294	-9.255	-12.040	-10.184
Dallas - Ft. Worth	-9.518	-8.859	-6.863	-7.852	-7.569	-9.067	-12.944	-9.349	-12.089	-10.272
Houston-Galveston	-8.772	-8.167	-7.147	-8.645	-7.789	-8.910	-13.497	-9.172	-12.246	-10.592
Atlanta, GA	-7.958	-7.266	-7.902	-7.827	-7.139	-9.380	-13.278	-10.417	-11.079	-9.484
Miami-Ft. Lauderdale-Hollywood	-9.320	-8.223	-7.244	-8.675	-6.978	-9.170	-13.311	-9.017	-11.643	-11.032
Seattle-Tacoma	-9.201	-8.198	-7.190	-9.279	-7.636	-9.502	-13.636	-9.869	-12.287	-8.298
Phoenix, AZ	-9.027	-7.935	-7.452	-8.640	-7.277	-8.273	-13.512	-9.674		-10.971
Minneapolis - St. Paul	-9.273	-8.052	-7.572	-8.642	-7.383	0.000	-13.336	-9.594	-11.250	-7.778
St. Louis	-8.842	-7.889	-7.265	-8.636	-6.901	-8.746	-13.096	-9.699	-11.310	
Tampa-St. Petersburg-Clearwater	-8.751	-7.318	-7.655	-8.843	-7.190	-8.834	-13.175	-9.692	0.000	-10.009
Denver - Boulder	-9.254	-8.564	-7.313	-8.625	-7.561	-8.575	-13.758	-9.812	-12.003	-11.061
Kansas City	-9.111	-8.301	-7.640	-8.236	-6.870	-8.573	-13.085	-10.117	-12.362	-9.116
Salt Lake City - Ogden	-9.498	-7.865	-7.523	-9.037	-7.724	-7.768	-14.192	-10.101		-9.522
Columbus, OH	-8.620	-7.851	-7.164	-8.400	-7.203	-8.532	-13.179	-9.521	-11.564	
Indianapolis, IN	-8.863	-8.040	-7.285	-8.378	-7.051	-8.689	-13.429	-9.452	-11.862	-8.328
Las Vegas, NV	-8.939	-8.279	-7.796	-8.035	-7.282	-8.695	-13.296	-8.825	0.000	-10.282
Memphis	-8.879	-7.924	-7.508	-7.908	-6.924	-9.414	-13.689	-9.251	-12.101	-8.636
Jacksonville, FL	-9.526	-8.268	-7.606	-8.368	-7.044	-9.158	-13.046	-9.858	-11.709	-
Honolulu	-8.773	-7.802	-7.376	-8.915	-7.245	-8.028	-13.977	-9.542	-12.223	-
Tulsa, OK	-9.135	-7.527	-7.480	-9.039	-6.935	-8.235	-13.468	-9.819	-11.512	-8.637
Albuquerque, NM	-8.708	-8.025	-6.815	-8.578	-6.836	-7.790	-13.103	-8.852	-13.063	-11.065
Spokane, WA	-8.726	-7.741	-7.533	-8.403	-7.808	-	-13.171	-8.891	-11.635	-
Boise, ID	-8.979	-8.153	-7.550	-8.189	-7.449	-	-13.191	-9.526	-13.227	-9.718
Jackson, MS	-8.778	-8.368	-6.883	-8.439	-6.856	-9.793	-13.399	-10.338	-12.106	-
Reno, NV	-8.570	-7.933	-7.034	-8.707	-7.158	-7.815	-13.222	-9.325	-	-10.412
Montgomery, AL	-8.926	-8.438	-7.199	-8.104	-6.829	-9.070	-12.791	-9.562	-11.403	-
Tallahassee, FL	-9.117	-8.039	-7.130	-8.722	-7.333	-9.436	-13.187	-9.840	-11.759	-
Anchorage, AK	-9.013	-7.689	-7.023	-8.485	-7.726	-8.417	-12.683	-9.605	-11.956	-
Columbus, GA	-9.360	-8.131	-7.113	-6.727	-5.630	-9.043	-13.433	-10.238	-12.219	-
Lubbock, TX	-8.616	-7.997	-7.318	-8.327	-6.512	-	-12.867	-9.843	-12.309	-10.442
Odessa - Midland, TX	-8.444	-7.875	-6.933	-8.119	-6.887	-7.801	-12.094	-	-12.325	-10.662
Amarillo, TX	-8.602	-7.991	-7.226	-8.310	-6.897	-8.083	-13.124	-8.585	-11.075	-10.433
Abilene, TX	-8.754	-7.583	-7.042	-8.298	-6.764	-	-12.309	-8.381	-11.720	-8.817
Monroe, LA	-9.190	-8.583	-7.202	-7.431	-6.888	-9.020	-13.432	-	-11.859	-
Billings, MT	-8.872	-7.440	-7.273	-8.013	-6.598	-	-12.584	-	-11.951	-
Albany, GA	-7.808	-8.627	-6.665	-7.713	-6.382	-8.967	-13.149	-9.451	-11.388	-
San Angelo, TX	-9.053	-7.009	-6.634	-8.368	-6.475	-	-12.845	-8.761		-10.474
Bismarck, ND	-8.186	-6.877	-6.997	-8.066	-6.702	-	-12.782	-8.706	-11.524	-
Meridian, MS	-8.293	-8.268	-7.067	-7.245	-6.892	-8.936	-12.866	-6.628	-10.817	-
Casper, WY	-9.116	-6.864	-7.024	-7.452	-6.514	-	-13.066	-8.870	-	-

Note: all coefficients are statistically significant at the 1% level

Table 7: Comparison of Changes in Share from Data and Simulations Using the Listener Demand Model

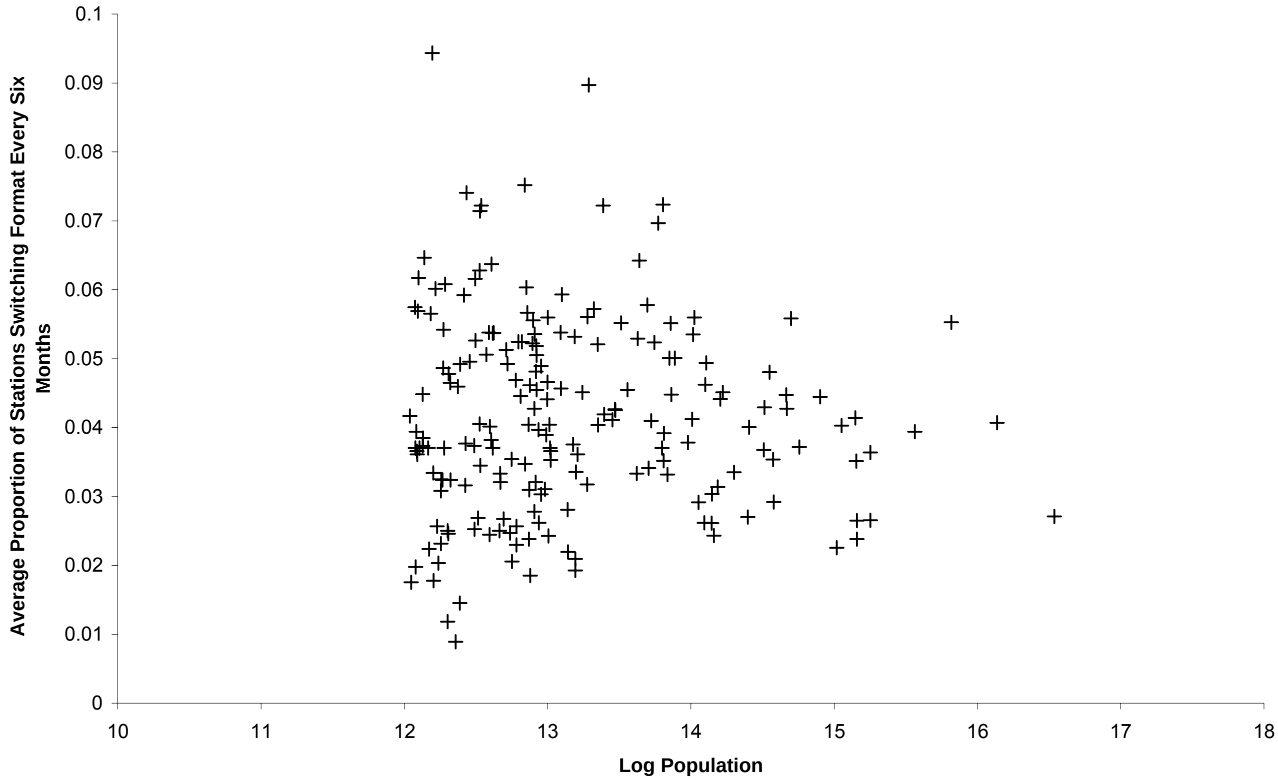
	Data	Simulation
Switching Stations (Obs: 508)		
Mean (x1000)	0.436	0.481
Standard Deviation (x1000)	2.324	3.183
Correlation for Individual Stations		
1 simulation	0.297	
Mean of 20 simulations	0.506	
Non-Switching Stations (Obs: 13983)		
Mean	-0.018	-0.087
Standard Deviation	1.172	3.538
Correlation for Individual Stations		
1 simulation	0.053	
Mean of 20 simulations	0.107	

Table 8: Estimates from Multinomial Logit Model for Estimating Station Conditional Choice Probabilities

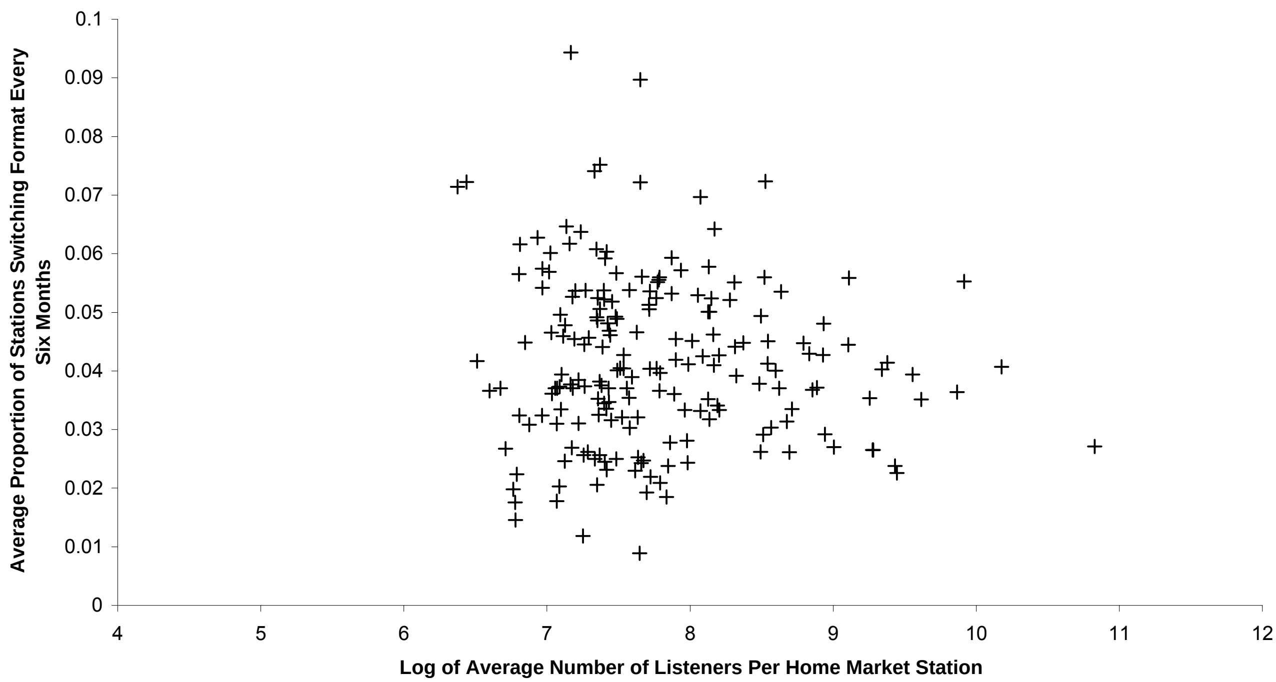
	AC	CHR	Country	Oldies	Rock	Urban	News	Other M	Religion	Spanish
Alternative	0.991	0.215	-0.77	6.125	2.898	1.726	7.779	-0.851	-2.058	-2.156
Format Dummies	(2.499)	(2.539)	(3.117)	(2.721)	(2.444)	(3.297)	(4.162)	(2.235)	(3.959)	(2.264)
Alternative	1.652	3.013	0.801	0.347	2.582	1.064	-1.769	-0.17	-0.141	0.272
Format Dummy	(0.746)	(0.899)	(0.727)	(0.739)	(0.808)	(0.744)	(0.723)	(0.713)	(0.740)	(0.728)
x FM Interactions										
Alternative Format	-2.055	-2.997	-1.26	0.051	-1.356	-0.43	0.277	-0.364	-4.384	0.303
x Proportion Hispanic	(1.773)	(1.836)	(1.882)	(1.872)	(1.815)	(1.990)	(1.865)	(1.795)	(2.185)	(2.517)
Alternative Format	-1.81	-1.857	-1.113	-2.572	-3.238	4.123	-0.254	-1.819	3.156	0.936
x Proportion Black	(1.324)	(1.364)	(1.363)	(1.549)	(1.478)	(2.953)	(1.379)	(1.356)	(1.678)	(1.719)
Alternative Format	0.06	-0.385	-0.124	0.149	-0.103	-0.095	-0.432	-0.129	-0.319	0
x Number of Other Stations	(0.083)	(0.157)	(0.134)	(0.216)	(0.108)	(0.169)	(0.138)	(0.150)	(0.174)	(0.077)
Alternative Format	15.001	3.543	16.584	-117.98	-23.297	-28.845	32.049	-4.662	-65.413	-4.207
xCombined Share of Other Stations	(17.449)	(21.820)	(14.064)	(47.847)	(18.783)	(23.539)	(21.469)	(21.184)	(47.013)	(23.846)
Alternative Format	0.075	0.16	-0.134	0.638	0.445	0.302	0.443	-0.187	-0.262	-0.275
x Market Format Quality	(0.252)	(0.294)	(0.394)	(0.286)	(0.295)	(0.390)	(0.307)	(0.214)	(0.332)	(0.231)
(from demand model)										
Alternative Format	-0.331	0.107	-0.133	-0.031	0.037	0.342	0.178	0.078	-0.017	-0.057
x Sum of Fixed Station Qualities	(0.093)	(0.165)	(0.132)	(0.238)	(0.123)	(0.169)	(0.119)	(0.160)	(0.172)	(0.080)
of other stations										
(from demand model)										
Current Format	-0.829	-0.895	-1.894	-0.921	-1.267	-1.394	-1.919	-0.983	-2.924	-1.974
x Switch Dummies	(0.946)	(0.967)	(0.953)	(0.975)	(0.950)	(0.969)	(0.971)	(0.951)	(0.981)	(0.983)
Other Variables										
Switch dummy	-3.854	(0.948)								
No other stations in format dummy	0.206	(0.234)								
Biggest station in current format dummy	-0.176	(0.325)								
Switch x FM interactions	-0.586	(0.779)								
Current Share x Switch	-155.753	(21.148)								
Current Unobs. Quality x Switch	-0.267	(0.081)								
Current Share x Switch to Dark	-1,211.75	(624.961)								
Current Unobs Quality x Switch to Dark	0.146	(0.517)								
Recent Switch (i.e., switch in last year)	0.051	(0.134)								
Observations	14,901									

Note: Also included are a full set of market x switch dummies. Standard errors in parentheses.

Figure 1: Relationship Between Population And Switch Rate



Relationship Between Switching Rate and Average Number of Listeners Per Station



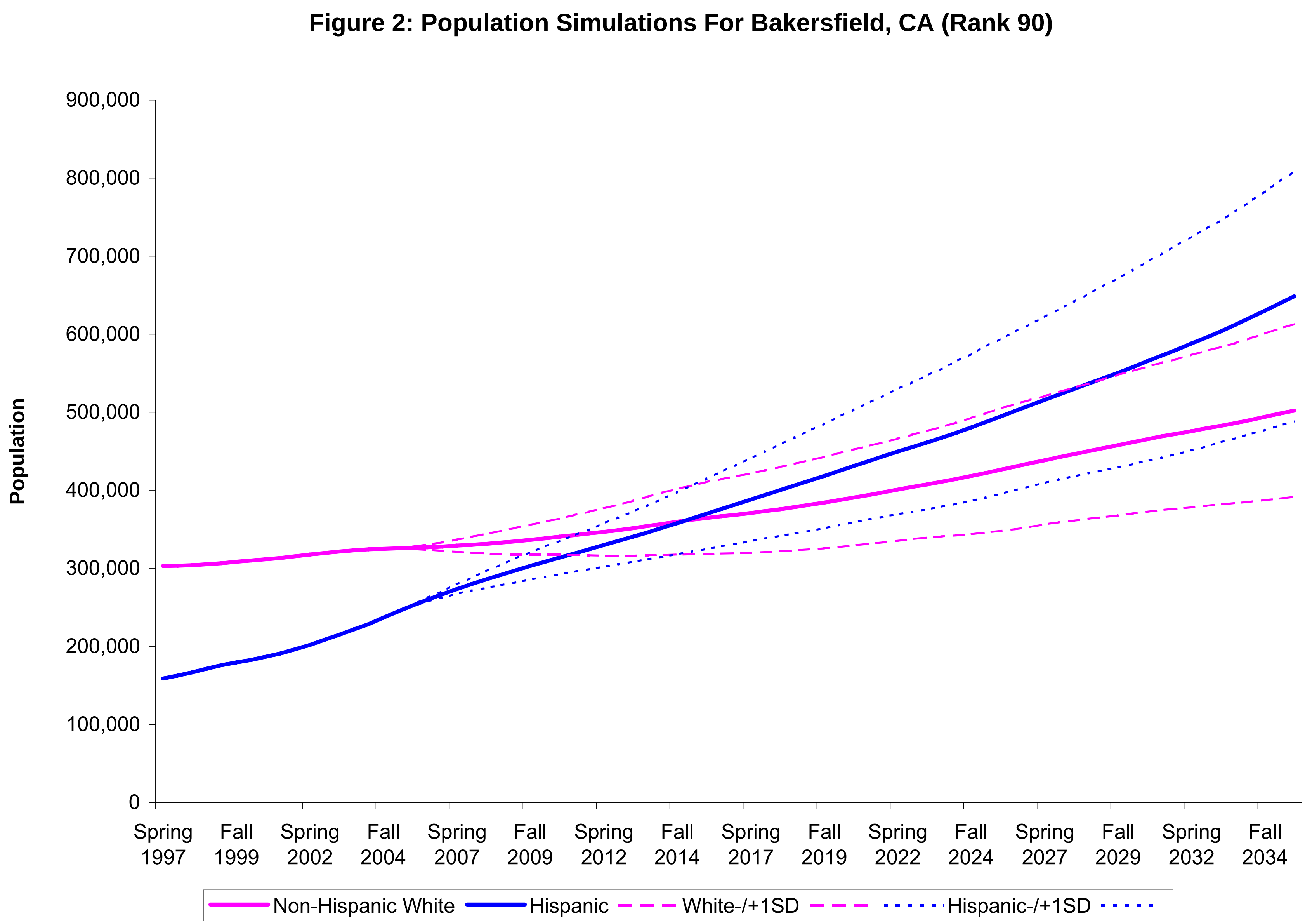
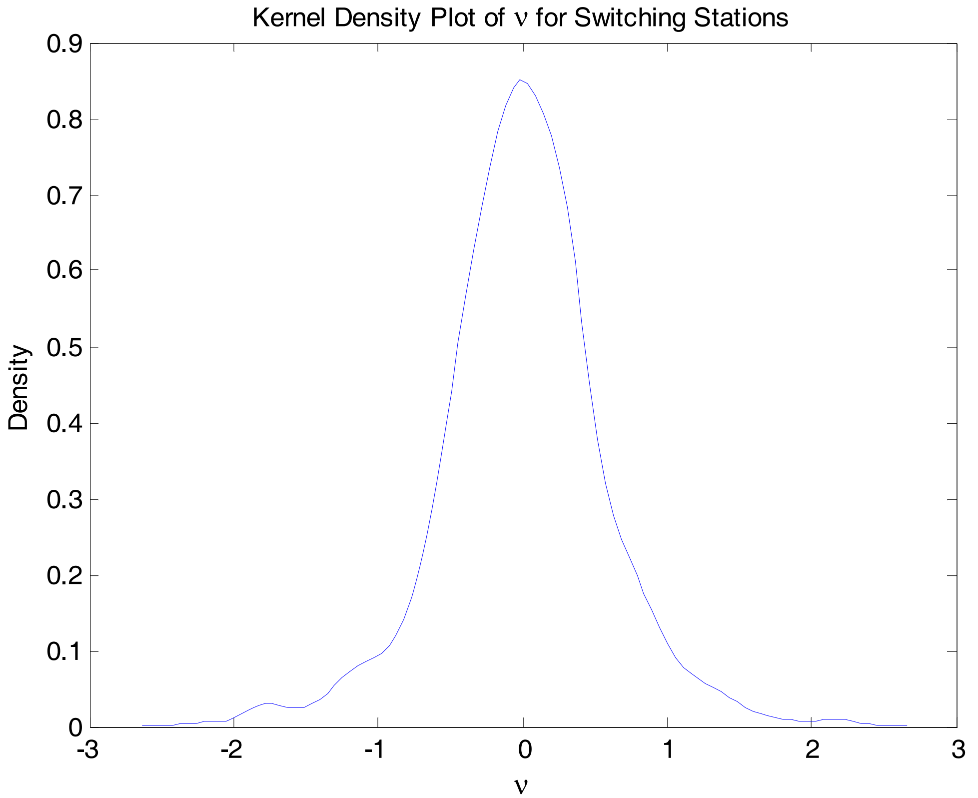


Figure 2: Population Simulations For Bakersfield, CA (Rank 90)
Population
900,000
800,000
700,000
600,000
500,000
400,000
300,000
200,000
100,000
0
Spring 1997
Fall 1999
Spring 2002
Fall 2004
Spring 2007
Fall 2009
Spring 2012
Fall 2014
Spring 2017
Fall 2019
Spring 2022
Fall 2024
Spring 2027
Fall 2029
Spring 2032
Fall 2034
Non-Hispanic White
Hispanic
White-/+1SD
Hispanic-/+1SD

Figure 3: Innovations in Station Quality



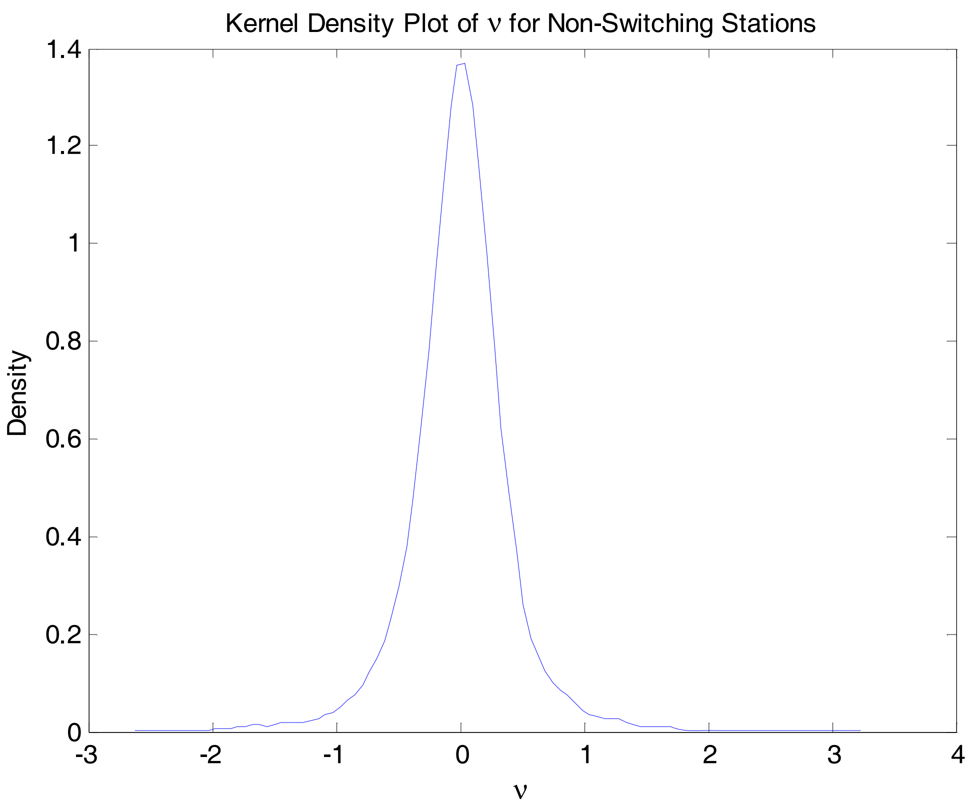


Figure 3 cont.: Empirical Distribution of Unobserved Station Qualities

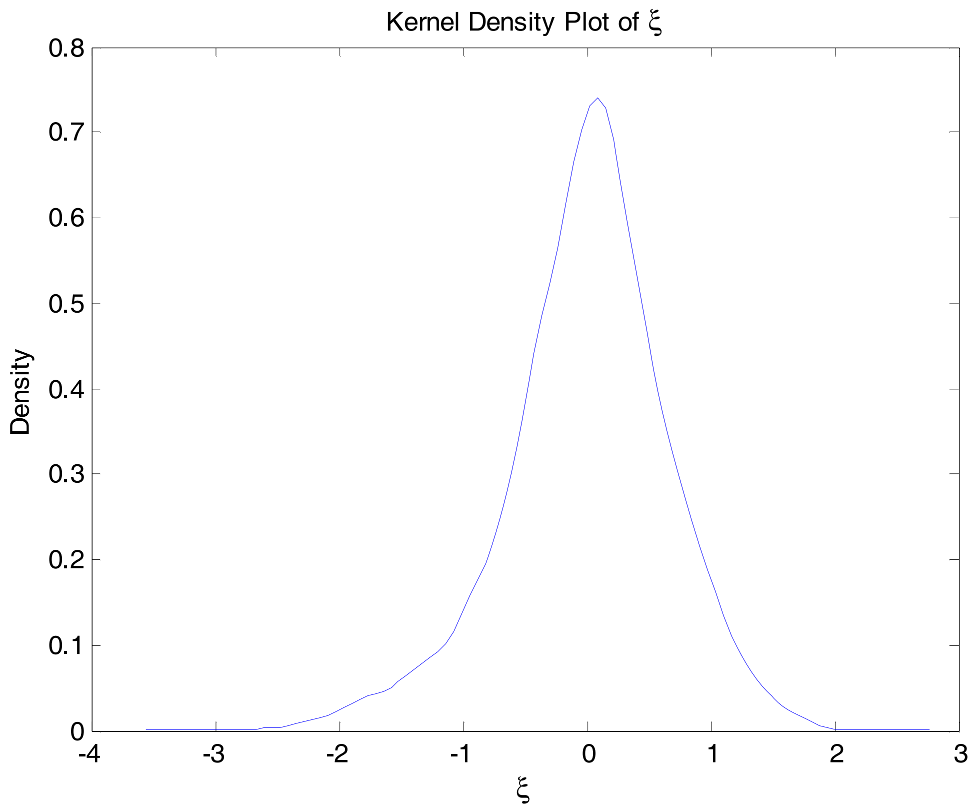


Figure 4: Simulated vs. Actual Changes in Share for Switching and Non-Switching Stations