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 costs incurred when radio stations change format (i.e., their positioning in a horizontally-differentiated products industry). The size of format switching costs have potentially important implications for merger and regulatory policy in this industry. Preliminary estimates indicate that sunk format switching costs are quite heterogeneous, increase with station audiences and market size, and are smaller for stations which have recently switched formats.

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1 Introduction

This paper estimates the costs of horizontal product repositioning (format switching) in the commercial radio industry. The paper has two main aims: first, to quantify costs which are potentially important for, *inter alia,* the design of merger and other regulatory policies in this industry and second, to extend and apply recent developed methods for estimating dynamic games to a setting with differentiated products. The paper also explores one way in which demand can be estimated in the presence of endogenous product characteristics. The method involves making assumptions on the timing of station format choices and innovations in station quality which are similar to those made in the recent literature on estimating product functions using firm-level data (Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2005)).

Firms may want to reposition their products to avoid competition or to react to or anticipate changes in demand. On the other hand, product repositioning may be costly if firms have to make an investment in redesigning their products or in advertising them to new consumers. In my setting an example of a repositioning is changing a station's programming from Rock music to Urban (rap, hip-hop etc.) music. The direct costs of e.g., changing a station's music library or hiring new DJs are likely to be small, but the costs involved in promoting the station to new listeners and advertisers may be large (Rock station audiences are predominantly white and male while Urban station audiences are largely black). The idea in the paper is to estimate the distribution of format switching costs by examining how stations respond to different (estimated) incentives to switch formats. Two features of the radio industry make it particularly suitable for this type of analysis. First, we can observe several thousand stations in independent local markets, so that even though the rate of format switching is relatively low (about 4.5% every six months) many switches are actually observed. Second, there are some sources of exogenous variation in station incentives to make particular switches. For example, Hispanic populations have grown faster in some markets than in others, providing differential incentives for stations to move into the Spanish-language format. Also, AM and FM stations are suited to different formats so that their expected profits from certain kinds of format switch differ systematically.

There are several reasons for being interested in the size of product repositioning costs. First, they play a potentially important role in determining how markets respond to demand and supply shocks. For example, if there is an exogenous demand shock (e.g., satellite radio) or an exogenous supply shock (e.g., the closure of a station due to FCC licence violations) then the distribution of repositioning costs will determine how far and how fast the set of products available in a market changes, and whether any gaps in the product space are filled in with consequences for welfare.

Second, product repositioning costs can play an important role in the evaluation of horizontal mergers. The Horizontal Merger Guidelines identify two potential constraints on the market power of merging firms: demand-side substitution, where price increases would lead customers to substitute to alternative products, or supply-side substitution, where they would lead to either new firms entering or existing firms repositioning their products to compete more closely with those of the merging firm. Supply-side substitution can only deter small but significant price increases if entry costs or product repositioning costs are small. In the radio industry, entry is difficult in most markets and substitution across formats by listeners and advertisers may be limited, so that (potential) reformatting may provide the main constraint on the market power of a firm dominating a format. The Department of Justice has used this logic in radio station merger cases and, based on its belief that the costs involved in format switching are large, it has challenged and required divestitures in mergers which would have increased concentration at the market-format level.[1]

Third, product repositioning costs may be one area in which common station ownership can produce significant efficiencies, by allowing firms to transfer expertise and contacts across stations

[1] For example, US Department of Justice (2000c), "format changes are unlikely to deter the anti-competitive consequences of this transaction. Successful radio stations are unlikely to undertake a format change solely in response to small but significant increases in the price being charged to advertisers by a multi-station firm such as Clear Channel." Klein (1997) describes the Department's view in the following way: "as we have learned through our investigations, the cost of these promotional expenditures and the loss of advertising revenue during the course of the format change while the station looks for new advertisers can be high. Picking up on this last point, the theory that says radio stations will jump in with new formats to defeat price increases makes the questionable assumption that it's as easy to change formats as it is changing clothes. But that grossly overstates the situation. As a practical matter, almost any existing station has invested time, money and effort to develop its format, audience and advertising base. If it decides to change its format, it must abandon at least some of these on-going relationships."

and across markets. Finally, there are several more theoretical reasons to be interested in the size of product repositioning costs. If repositioning costs are fixed/sunk then repositioning may be socially excessive (Mankiw and Whinston (1986), Berry and Waldfogel (1999)). Judd (1985) shows that entry deterrence through product proliferation is only credible if product exit (or repositioning costs) are large.

1.1 Related Literature

1.1.1 Estimation of Dynamic Oligopoly Models

Several recent papers (Aguirregabiria and Mira (2006), Bajari, Benkard and Levin (2006, BBL), Berry, Pakes and Ostrovsky (2006) and Pesendorfer and Schmidt-Dengler (2006)) have proposed methodologies for estimating dynamic oligopoly entry and exit-type models with Markov Perfect Nash Equilibria. A common theme in these papers is that it is possible to estimate the parameters of the game using observed firm behaviors without having to solve for the equilibrium which may be hard or, with many firms, impossible. The method I use in this paper is closest to the two-stage approach suggested by BBL, which builds on the earlier work of Hotz and Miller (1993) and Hotz et al. (1994) in the single agent setting.

Ryan (2005), Ryan and Tucker (2006), Beresteanu and Ellickson (2006), Maciera (2006) and Collard-Wexler (2005) have applied these dynamic models to actual industry data. Ryan (2005) and Collard-Wexler (2005) examine the homogenous product cement and ready-mix concrete industries. Beresteanu and Ellickson (2006) and Maciera (2006) use logit demand models to allow vertical product differentiation in the supermarket and supercomputer industries. In the radio industry both horizontal product differentiation, based on observable station programming, and vertical differentiation are important and I use a rich random coefficients demand model to capture these effects.

A comment is also in order about why I use a dynamic model to estimate format switching costs. Stations change formats infrequently so a format switch will be based on expectations of profits accruing over a number of future periods during which the market may evolve in different ways. A dynamic model is an attempt to “account” for expected future benefits correctly. It also allows for the possibilities that (i) stations may have an option value to waiting before making a costly format switch and (ii) a format switch is only profitable because a station expects it to lead to other stations changing format in the future. A static, simultaneous move model would not allow for either of these possiblities.

1.1.2 Format Differentiation and Switching in the Radio Industry

There has been some previous work on format choices in the radio industry. Romeo and Dick (2005) analyze the success of format switches in increasing station performance. Consistent with my data, they find that stations making major formats changes are able to increase their listenership, particularly when moving into formats where there are few competitors. Tyler Mooney (2006) estimates static models of listener and advertiser demand to examine how welfare changed in the industry in the late 1990s. She estimates that welfare increased over time, partly because stations have switched into formats serving listeners who are more valued by advertisers.

Berry and Waldfogel (2001) and Sweeting (2006) also analyze horizontal differentiation in the radio industry with a particular emphasis on the effects of common ownership. Both papers provide evidence that owners owning multiple stations in the same market differentiate their stations and that owners of multiple stations in different markets may tend to offer more similar stations, presumably to exploit economies of scope. While the current version of this paper is relatively silent on these effects, I hope to say more about the effects of common ownership on switching costs and operating costs in future versions.

1.2 Outline

The paper is structured as follows. Section 2 describes the data. Section 3 presents a descriptive analysis of format switching. This shows both that there is considerable format switching and that stations seems to move in response to quite small opportunities to gain listenership. Section 4 describes the formal model and Section 5 details the estimation procedure. Section 6 provides some preliminary results and Section 7 concludes.

2 Data

The main source of data used in the analysis comes from BIAfn's *MediaAccess Pro* database. This database, which is also used by the FCC in analyzing the radio industry, contains data on station characteristics, station ownership history, Arbitron ratings and BIAfn's own estimates of station and market advertising revenues. I have data covering the period Spring 1996 to Spring 2006 from the 2001, 2002 and 2006 versions of the BIA database. I drop the data for 1996 as many station formats are missing. 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*.

The BIAfn database includes some information (but not ratings data) on non-commercial stations (e.g., public stations and those owned by educational organizations). I only use the data on commercial stations.[2]

2.1 Formats

I use ten format categories to define a station's programming. BIAfn database uses 20 format categories to categorize station programming. Some of these format categories, such as Rock and Album Oriented Rock/Classic Rock, are actually quite similar (Sweeting (2006) shows this using station playlists) and appeal to similar demographics. The costs of switching between these formats should be small as the station is likely to be able to keep most of its old listeners and advertisers. I therefore aggregate these format categories together to produce a grouping of 10 formats. I also define another format "Dark" for stations which are temporarily off-air.

Table 1 lists the formats which I use, together with the associated BIAfn format categories, and

[2]Future versions will use data on the presence of NPR stations in particular formats. Berry and Waldfogel (1999c) provide evidence of a crowding out effect where the presence of public stations leads to fewer commercial stations in certain formats, such as Jazz.

measures of the average listener demographics in each format. The formats used clearly appeal to different demographic groups based on age, sex and ethnicity/race.

At several points in the paper I use the term "contemporary music" to refer to the formats Adult Contemporary, CHR/Top 40, Country, Oldies, Rock and Urban. The Other Music format includes some primarily music formats such as Jazz and Big Band, but also includes formats like Middle of the Road and Full Service which are a mixture of music and talk. Table 1 shows that the contemporary music formats are largely composed of FM stations, whereas AM stations are predominant in News, Other Music and Religious programming.

2.2 Geographic Markets and Demographic Data

One of the appealing features of the broadcast radio industry for empirical analysis is the existence of many local geographic markets. I use Arbitron-defined metro-markets, which are the industry standard and are now also used by the FCC and Department of Justice. These markets typically correspond to MSAs. I use the markets which were in Arbitron's top 199 markets by population in 2001. From this set I drop Puerto Rico and Honolulu, which have unusual ethnic/format mixes, and Westchester, NY which ceased to be monitored by Arbitron in 2004. Three markets on the Gulf Coast (New Orleans, Biloxi and Beaumont) have no ratings data in Fall 2005 following Hurricane Katrina.

Each station in the data has at most one "home" market. In some markets, there are a number of out of market stations which have significant listenership. This feature is particularly common where a market is close to a much larger market nearby. For example, 25% of radio listening in Providence, RI in Fall 2002 was to stations which are home to the Boston market.

I use the annual County Population Estimates from the US Census to measure market demographics.[3] To match the demographic-level station listenership data I use 10 age-sex groups (ages 12-24, 25-34, 35-49, 50-64 and 65 plus for both males and females) and for each age-sex group, 4 eth-

[3] The estimates come from July of each year, so I use the numbers for both the Spring and Fall quarters.

nic/racial categories (non-Hispanic white, non-Hispanic black, Hispanic white and Hispanic black). Market-level demographics are calculated by matching counties to markets using the 2005 Arbitron market definitions.[4]

The markets differ quite widely in their ethnic/racial mixes. The percentage of the population that is black varies from 0.2% in Wausau-Stevens Point,WI to 45.2% in Jackson, MS, while the percentage of the population that is white or black Hispanic varies from 0.4% in Charleston, WV to 86.2% in McAllen-Brownsville, TX.

2.3 Listenership

The BIAfn database reports Arbitron data on station listenership. Arbitron estimates each station's share of radio listening by asking a sample of listeners in each market to record their listenership in a diary.

I use two different types of share data. First, for every market-quarter I have Arbitron's estimate of each station's share of radio listening amongst listeners aged 12 and above during a broadcast week of Monday-Sunday 6am-midnight. I multiply these market shares by Arbitron's APR rating for each market-quarter, which measures the proportion of the 12+ population listening to radio, to calculate each station's market share where the market is the time available to every person aged 12 and above during the broadcast week.[5] Listening to non-commercial stations is therefore included in the outside good of not listening to radio. One important issue that arises is that Arbitron only lists share data for stations with enough listeners to meet its Minimum Reporting Standard. The exact set of stations meeting these requirements varies from quarter to quarter and has expanded slightly over time as Arbitron has expanded its sample sizes. When estimating the random coefficients model of demand I assume that non-listed stations in a market have market shares which are equal to one

[4] In a few cases an Arbitron market only includes part of a county, in which case I scale the population estimates from the complete set of counties using Arbitron's own market population estimates. Arbitron updates its market definitions relatively rarely, mainly after the decennial census.

[5] The APR numbers are 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.

quarter of the smallest listed station. In future versions I will investigate the robustness of the results to this assumption.

The second type of share data is demographic-specific listening data from Spring 2006. This data lists the number of listeners a station has amongst a specific age-sex group. The age groups are 12-17, 18-34, 18-49, 25-34, 25-49, 25-54, 35-44 and 35-64. By combining these numbers I produce station shares for 10 age groups, 12-24, 25-34, 35-49, 50-64 and 65 plus for both males and females. The Minimum Reporting Standard also applies to these data and I use the same imputation procedure as before.[6]

The BIAfn data does not contain ethnicity/race-specific share data. As I explain in Section 5 I also make use of two types of additional information on racial listening. Arbitron's *Radio Today* publications provide estimates of the proportion of listeners to each format who are black or Hispanic for Spring 2003, 2004 and 2005 for a set of formats that match the ones which I use closely. These numbers are based on a set of markets where Arbitron tracks ethnic listening. For a similar set of markets Arbitron also provides estimates of total listening by racial ethnic/group in Fall 2004 on its website.

2.4 Advertising Revenues

The BIAfn database also provides estimates of annual station and market advertising revenues. The station estimates are derived from the market estimates using a proprietary BIAfn formula, and they track changes in market revenue and station listenership very closely. Currently I only use the revenue estimates to calibrate the value of different types of listener to stations. In the future I will use the data on the quantity of advertising for music stations used in Sweeting (2006) to explicitly model the advertising market. Tyler Mooney (2006) finds sensible estimates of advertiser demand and the disutility of listeners for advertising when she matches her model to the summary statistics reported in Sweeting (2006) and market-level estimates of per minute advertising prices reported by Spot Ratings

[6] When using the demographic differenced moments described below I only the mean utilities for those stations with non-missing share data. However to calculate those mean utilities I need to use the share information for all stations.

and Data Services.

2.5 Station Entry and Exit

Many industries have high entry and exit rates and these may drive changes in product differentiation. In the commercial radio industry station entry and exit is rare. Entry is limited by both spectrum constraints, which prevent entry in larger markets, and by the need to secure FCC approval for new stations with only a small number of applications being approved. In the 196 markets I use in the analysis there are 230 cases of entry by commercial stations in the decade after 1997, compared with 4,395 stations active in 1997. Most of the entrants have relatively low power transmitters and low market shares compared with existing firms, although there are a few examples of new entrants rapidly gaining significant market share. The difficulty of entry means that exit is also rare, although sales of existing stations to new owners are common. There are 37 cases of exit during my sample period. A review of FCC documents indicates that most of these exits followed licence withdrawals by the FCC following licence violations.[7]

In my model I treat the number of stations in a market as fixed and treat entry and exit in the same way as stations temporarily going inactive ("Dark"). In future versions of the paper, I intend to model entry and exit separately although it is worth noting that however I treat them, entry and exit decisions are likely to look quite random.

2.6 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

[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.

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 largely abstract from common ownership, except for controlling for its effects when I estimate station policy functions.

3 A Descriptive Analysis of Format Switching

This section provides a descriptive analysis of station format switching with particular emphasis on those features of the data which are potentially useful in identifying format switching costs.

Table 2 provides some summary statistics on station format and format switching choices. The stations used are 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. There are some switches into and out of each format. The Spanish-language format has the largest proportional gain in stations, which is to be expected given the increase in Hispanic populations in many US markets. Country, Oldies and Other Music (which includes relatively "old fashioned" formats such as Middle of the Road and Easy Listening) have experienced the greatest net exit.

The table distinguishes between AM and FM stations. AM stations are concentrated in non-contemporary music formats, which makes sense given the relative advantage of the FM signal for music programming, and they are also less likely to switch to contemporary music formats. This difference between AM and FM stations is potentially useful in identifying format switching costs.

The table also shows a measure of the average listenership of stations in each format. As explained beneath the table, this measure is calculated to correct for the possibility that some formats may be systematically more popular in markets with fewer stations. Comparing AM and FM stations, we see that AM stations tend to have higher shares in non-contemporary music formats, consistent with these formats being the ones where the AM signal provides the highest relative quality. There are also some formats in which stations tend to have higher shares whatever the band. For example, Urban and CHR/Top 40 stations tend to have more listeners than Rock stations. The most obvious interpretation 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 it takes fewer listeners per station to support a Rock station than an Urban or CHR/Top 40 station. The relatively small number of listeners per Spanish-language station may reflect the expected future growth of Hispanic populations. 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 being able to use relative cheap programming (e.g., broadcast of religious services).

Table 3 compares the listenership of format switching and non-switching stations. As Dark stations have no listeners I do not use Dark stations or stations switching to or from Dark. I also only use those stations with enough listeners to be rated by Arbitron. Switching stations typically have fewer listeners than non-switching stations and tend to increase their listenership in the two quarters following a switch. On average, switching stations increase their listenership by a statistically significant 13% in the year (two quarters) following the switch.[8] The listenership of non-switching stations tend to falls, partly because they lose listeners to switchers but also because listening became less concentrated during the time period of the data. The significant increase in share for switchers is consistent with stations switching formats in order to gain listeners (and thereby generate advertising revenues) and with the existence of small, but significant switching costs which prevent stations from switching in response to smaller expected gains. It is also noticeable that the standard deviation of the change in share for switchers is only slightly greater than the standard deviation in the change in share for non-switchers. This suggests that switching is not particularly "random" (i.e., we do not see stations making particularly bad switching decisions) and that there is not too much uncertainty

[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.

about how a station will perform in its new format.

The table also reports the average Arbitron market rank for switchers and non-switchers. The market rank is 1 for the largest market based on population in 2001 (New York City), 2 for the next largest (Los Angeles) and so on. Switchers and non-switchers come from markets of similar sizes. If switching costs were invariant with market size then one might expect more switching in larger markets where the costs per listener would be smaller. This result therefore suggests that switching costs may increase with market size or with the number of listeners that a station has. This is plausible if switching costs include the costs of advertising to attract new listeners.

Tables 4-6 investigate how far observable market features can explain (changes in) the distribution of stations across formats. Given that we can only try to estimate switching costs by looking at how stations respond to measurable opportunities to increase their discounted future profits based on observables, this exercise will clearly be futile if observables have no explanatory power for stations' format choices.

Table 4(a) reports the results of a set of 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 demographic characteristics, a set of region dummies and the combined share of out of market stations. This variable is included to see whether home market stations tend to avoid formats where there is significant competition from out of market stations. Obviously the amount of listening to out of market stations is likely to be endogenous to the format choice of home market stations. I therefore create an instrument for the variable, the predicted share of out of market stations. To do this I first 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.[9]

[9] 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

The pattern of the coefficients is sensible. The race coefficients are consistent with the ethnic/make-up of audiences shown in Table 1 with, for example, higher black populations associated with fewer Country and Rock and more Urban and Religious stations. Hispanic populations have a large effect on the proportion of Spanish-language stations. Most of the age and sex coefficients are insignificant, which is consistent with a lack of variation in these variables across markets, although, as expected, markets with more females have more Religious stations. The region dummies reveal that there are more Country and Religious stations in the South than in New England. Four out of the ten 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 leads to format switching in the expected directions. Five out of the ten out of market coefficients are negative and significant and 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.

Tables 4(a) and (b) use the proportion of stations in a market-format as the dependent variable. In Table 5 I examine the ability of observable variables to predict format switching by individual stations. This is done by estimating a multinomial logit model where a station's choices are the eleven different formats. The explanatory variables include the sum of shares of other home market stations in 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.

format, the sum of shares of out of market stations in the format and a measure of the attractiveness of the format. This attractiveness measure is the prediction of total market-format-quarter's share based on a linear regression of market-format-quarter shares on the demographic variables and region dummies used in Table 4(a) as well as a full set of quarter dummies. The difference between this prediction and the combined sum of stations' shares already in the format can be thought of as a measure of the market opportunity for a station. All of these variables are interacted with a dummy indicating the station's current format in case there are different effects of the variables for a station remaining in its current format and for one switching formats. All of the variables are set to zero for the "Dark" format. Also included are the station's own share in its current format, a measure of the median share of stations in the market, an indicator for whether the station is the largest in its format, and a set of dummies representing different types of format switch (interacted with the band of the station), some ownership related variables and a dummy for whether the station has recently switched formats.

The coefficients in Table 5 show a sensible pattern. In particular, a station is more likely to stay in and to move to a more attractive format (predicted format share coefficients positive) where the combined listenership of other stations, both from the market and out of the market, are small. To understand the size of the implied effects, consider the example of the average AC station in the sample. The average probability of an AC station switching to another format before the next quarter is 0.046. A one standard deviation increase from the mean in the predicted format share for AC reduces this probability by 0.005 (10%). A one standard deviation increase in the share of other home market AC stations increases the probability of switching by 0.009 (18%). A one standard deviation increase in the mean of the predicted format share of Rock increases the probability of an AC station switching to Rock from 0.009 to 0.012 (30%).

A station with a larger share in its current format, relative to the median share of a station in the market, is less likely to switch formats. A one standard deviation increase in a station's share from the mean decreases the probability of switching for an AC station from 0.046 to 0.014 (60%).

A station which has switched formats in the previous two quarters is more likely to switch again (probability increases from 0.046 to 0.057). This is consistent with a station having to spend resources over a number of quarters to attract new listeners and advertisers. If a station is going to have to spend resources in establishing itself in its current format, then the additional cost of switching to a different format will be lower.

The coefficients on all of the switching dummies are negative and highly significant, consistent with stations being much more likely to stay in their own format than making any particular switch. The relative size of the coefficients themselves reflect the fact that AM stations are more likely to switch to non-contemporary music formats than FM stations, consistent with FM being relatively better for contemporary music, and that both types of station rarely become inactive (Dark).

Most of the coefficients in Table 5 are highly statistically significant, suggesting that observable variables do have some explanatory power for switching decisions. At the bottom of the table I compare the value of the log-likelihood including all of these variables with the value of the log-likelihood when I only include a dummy variable for whether there is a switch of formats. Including the additional variables makes the log-likelihood increase substantially, and, considering the dummy for switching as being like a constant, the pseudo-R^2 would be 0.094. While this pseudo-R^2 is quite large compared with those usually estimated for entry and exit models, it also implies that individual switching decisions also look quite random from the perspective of the researcher.

4 Dynamic Model of Format Switching

This section presents the model of the industry. I start by describing the state space and then outline my assumptions on the timing of station format switching decisions and how the state space evolves. These assumptions are important in justifying how I estimate demand given the potential endogeneity of product characteristics. I then outline how station payoffs are determined.

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 (ii) a set of private information payoff "shocks" that affect a station's payoff from choosing to be in a particular format in a particular quarter. For ease of notation I use $\mathcal{S}$ to refer to the observable state space.

4.1.1 Station Characteristics

There are N_m stations in market m. Each station is in exactly one format in each quarter. There are eleven available formats (F): the ten formats listed in Table 1 and the format "Dark" (0) in which a station is inactive. Stations have three observable characteristics which are assumed to be fixed over time: whether they are home to the market or out of market, the station's band (AM or FM) and, for home market stations, the proportion of the market's population which can receive the station's signal.[11] Each station also has a quality component ξ_s which can change over time. Unlike the other station characteristics, this is not directly observable in the data but is backed out through estimation of a model of listener demand.

4.1.2 Market Characteristics

Each market m is in a geographic region r. Its population is divided into 40 demographic groups (5 age categories x 4 ethnic/race categories x 2 sex categories). There is a growth rate for three ethnic/racial groups (non-Hispanic white, non-Hispanic black and Hispanic (including blacks and whites)). Each market is also associated with a particular advertising price per listener.

4.1.3 Format Characteristics

Each active format f has an average attractiveness to listeners which is the same across regions. Formats also differ in their attractiveness to different demographics and in different geographic regions.

[11] This treatment ignores the possibility that a station could invest to increase signal strength.

4.2 Timing

There are an infinite sequence of periods. I call these periods "quarters" although I treat them as being six months long as I only use data from the Spring and Fall 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 for the current quarter are realized; and,

4. station formats change according to station format choices. Other features of the state space 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

Each station has a quality which does not depend on observables such as signal coverage. One might think of this quality as representing programming quality but it could also reflect any other influence on listener tastes for the station. This quality is assumed to evolve stochastically according to AR(1) processes. Specifically, I assume that for a station which does not change formats

$$\xi_{smt} = \rho^{\xi}\xi_{smt-1} + \mu_1^{\xi} + \upsilon_{1smt} \tag{1}$$

where $\upsilon_{1smt} \sim N(0, \eta_1^{\xi})$. For a station changing formats I assume that

$$\xi_{smt} = \rho^{\xi}\xi_{smt-1} + \mu_1^{\xi} + \mu_2^{\xi} + \upsilon_{1smt} + \upsilon_{2smt} \tag{2}$$

with $\upsilon_{2smt} \sim N(0, \eta_2^{\xi})$ so that I allow for a format switcher to experience an additional fixed and random change in its quality. A motivation for this specification is that a station switching to a new format may lose some of the expertise it has gained from operating in its old format and there may also be a degree of unpredictable (from the station's perspective) randomness in how well-suited it is suited to its new format. It is an assumption that stations do not know the realization of their own or other stations υ_{st}s when they make their format choices for the next period.

As already noted, a station may appear in multiple markets. I (currently) assume that the ξ_{smt} evolves independently across markets.

4.3.2 Market Demographics

In each market there are 40 different demographic groups based on combinations of age, sex and ethnicity/race. As the age and sex composition of each market is quite similar and changes relatively little over time, I focus on changes in the ethnic/racial make-up of each market. I allow the *growth rate* for three ethnic/racial groups e (non-Hispanic white, non-Hispanic black and Hispanics (including Hispanic blacks)) to evolve according to the following AR(1) process:

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

where $\upsilon_{emt} \sim N(0, \eta^e)$. 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 apply the growth rate for ethnic/racial group e to each one of the 40 groups in the market which are of ethnicity/race e. I assume that the parameters are the same across the ethnic/racial groups: this implies that in the long-run the proportion of the population in each ethnic group is also stationary.

4.4 A 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

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

where $l_{sdt}(\mathcal{S})$ is the number of listeners the station has in demographic d and p_{dm} is the "price" of a listener in market m. As noted above, the advertising market will be modelled more explicitly in future versions. The parameter 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. Note that this is the cost in addition to the expected quality loss (μ_2^{ξ}). $\varepsilon_{st}(f_{st+1})$ 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 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.

Currently I assume that stations only earn revenues from listeners in their home market. We should not expect this to be exactly true but on average, a station which is rated in multiple market has 80% of its listeners in its home market and regressions using BIAfn's estimates of station revenues indicate that, on average, an out of market listener generates about one-fifth as much revenue as a home market listener. This is consistent with most radio advertising being done by local retailers who are unlikely to value reaching consumers living outside of the market.

4.4.1 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

$$u_{imst} = \beta_i^C + F_s \beta_{imt}^F + X_{sf_s} \beta^S + \xi_{smt} + \varepsilon_{ist} \tag{5}$$

where F_s is a row vector indicating the current format of station s. β_i^C captures the individual's taste for any commercial radio station, and I assume that $\beta_i^C = \overline{\beta^C} + v_i^C$ where $v_i^C \sim N(0, \sigma_C^2)$. β_{imt}^F captures an individual's taste for a format which can vary with individual demographics (D_i), geographic region and time as well as randomly across individuals.

$$\beta_{imt}^F = \overline{\beta^F} + \Pi^D D_i + \Pi^R R_m + \Pi^T T_t + \Sigma v_i^F \tag{6}$$

I assume that demographic effects on tastes are additively separable in discrete variables measuring age, sex and ethnicity/race. I assume that the v_i^Fs are IID standard normal and independent of the included demographics, region and time. I also assume that the random component of β_{imt}^F is independent across formats i.e, that Σ is diagonal. This assumption should be relaxed as listeners may be more likely, for example, to substitute between two stations in different contemporary music formats than between a contemporary music station and a religious station.[12]

X_{sf_s} are the fixed characteristics of station s, such as its home market status, band and signal coverage. Home market and band are interacted with a station's format to allow listeners to value,

[12] Note that β_i^C, the random coefficient on the constant, allows there to be more substitution between commercial radio stations than between listening and the outside good of not listening to commercial radio.

for example, an AM station in the Top 40 format less than an AM in the News/Talk format all else equal. ξ_{smt} is the component of quality of station s which does not depend on observable variables. All listeners are assumed to value these observed and unobserved quality characteristics in the same way (i.e., there are no random coefficients on the parameters associated with these variables).[13]

Finally, ε_{ist} is a Type I extreme value term providing random variation in listener tastes across individual stations.

4.5 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, 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.[14]

Formally, a station's Markov Perfect strategy is a function ς_s which maps from the observable state space and the station's own payoff shocks εs to actions (format choices), i.e., $\varsigma_s : \mathcal{S}$ x $\varepsilon_s \rightarrow A_s$. A profile of Markov Perfect strategies for all stations is $\varsigma = (\varsigma_1, \varsigma_2, ...)$, $\varsigma : S$ x ε_1 x ε_2 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

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

[13] Of course, listeners will value a station quite differently depending on whether they are in the signal coverage area or not. However, without share information on different locations within a market with varying signal coverage, it is very hard to model this effect.

[14] 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.

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 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 Markov Perfect strategies is a Markov Perfect Equilibrium when each station's strategy is optimal given the strategies of other stations.

5 Estimation

I follow a two stage estimation approach similar to that proposed by BBL. The first stage involves the estimation of listener demand, the stochastic state transitions and station policies. In the second stage, I use forward simulation to estimate the components of stations' expected future payoffs when making different format choices and use these estimates to find the parameters of (4). Consistent with most of the literature in this area I do not estimate the discount factor β but instead assume that it is 0.95.

5.1 First Stage: Demographic Transitions

Equation (3) is estimated using the market demographic data described in Section 2. To prevent some very small ethnic/racial groups, which occasionally show very high proportional increases or declines having an excessive effect on the estimates, I only use observations on ethnic groups with at least a 5% share of market population. The estimated parameters are

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

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

Figure 1 shows the changes in the ethnic/racial composition of Raleigh-Durham, NC when I simulate population forward from Fall 2005 using this model of population growth. Raleigh-Durham's Hispanic population has grown rapidly in recent years, reaching 7.4% of the population in 2005. When I simulate forward, this growth tends to continue for a few more years, but is, on average, slow after 2010 when the growth rates of the different ethnic groups tend to converge.

5.2 First Stage: Listener Demand and the Evolution of Unobserved Station Qualities

Listener demand and the evolution of station qualities are estimated using the Arbitron data on station listenership described above. The standard estimation approach for random coefficient demand models (as described, for example, by Nevo (2000)) assumes that observed product characteristics, such as formats, are exogenous. This assumption is clearly problematic for an analysis of the choice of product characteristics. Fortunately given my assumptions on the evolution of unobserved station quality and the timing of station format choices I am able to use a quasi-differencing approach to isolate the innovations in station quality which are unknown when stations make their format choices for the next period.[15] I use these innovations to form a set of moment conditions used in estimation.

5.2.1 Quasi-Differenced Moments

The "mean utility" of station s in market m at time t (taking out those components of tastes which vary across people within a market) is

$$\delta_{smt} = \overline{\beta^C} + F_s\left(\overline{\beta^F} + \Pi^R R_m + \Pi^T T_t\right) + X_{sf_s}\beta^S + \xi_{smt} \qquad (10)$$

[15] This approach is quite similar to recent approaches used to analyze firm-level productivity literature (Olley and Pakes (1996), Levinsohn-Petrin (2003) and Ackerberg et al. (2005)). The idea is mentioned in the original Berry et al. (1995) demand paper although I am not aware of any previous attempts to apply it.

An endogeneity problem arises because the unobservable component of station quality ξ_{smt} may be correlated with station format choices. For example, the Country format may tend to attract "better" stations in the South, where Country music is popular, than it does in New England or stations may avoid competing directly with high quality competitors. To reduce the notation I denote $\overline{\beta^C} + F_s\left(\overline{\beta^F} + \Pi^R R_m + \Pi^T T_t\right) + X_{sf_s}\beta^S$ as $\widetilde{X_{smt}}\beta$, so that $\delta_{smt} = \widetilde{X_{smt}}\beta + \xi_{smt}$.

Recall that for a station that does not change formats

$$\xi_{smt} = \rho^{\xi}\xi_{smt-1} + \mu_1^{\xi} + \upsilon_{1smt} \tag{11}$$

and that when s chooses its format for quarter t (in quarter $t-1$) the value of the quality innovation υ_{1smt} which occurs between $t-1$ and t is unknown. Given values for the mean utilities and the parameters it is possible to calculate υ_{1smt} by taking a quasi-difference.

$$\upsilon_{1smt} = \xi_{smt} - \rho^{\xi}\xi_{smt-1} - \mu_1^{\xi} \tag{12}$$

$$= (\delta_{smt} - \rho^{\xi}\delta_{smt-1}) - \left(\widetilde{X_{smt}} - \rho^{\xi}\widetilde{X_{smt-1}}\right)\beta - \mu_1^{\xi} \tag{13}$$

For stations which change formats we can also isolate the unexpected innovation in station quality

$$\upsilon_{1smt} + \upsilon_{2smt} = \xi_{smt} - \rho^{\xi}\xi_{smt-1} - \mu_1^{\xi} - \mu_2^{\xi} \tag{14}$$

$$= (\delta_{smt} - \rho^{\xi}\delta_{smt-1}) - \left(\widetilde{X_{smt}} - \rho^{\xi}\widetilde{X_{smt-1}}\right)\beta - \mu_1^{\xi} - \mu_2^{\xi} \tag{15}$$

These innovations should be uncorrelated with station formats at both t and $t-1$ so I can form the following moment conditions

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

where θ are all of the parameters of the demand system and quality transitions, $\widehat{\upsilon}_{smt}(\theta)$ is $\widehat{\upsilon}_{1smt}$ or $\widehat{\upsilon}_{1smt}+\widehat{\upsilon}_{2smt}$ depending on whether the station changes format or not, and Z_{smt} is a set of instruments.

For given values of the non-linear demand parameters the δs are solved for using the contraction mapping proposed by Berry et al. (1995) which matches predicted and observed market shares.[16] The instruments include the observed station and market characteristics in $\widetilde{X_{smt}}$, $\widetilde{X_{smt-1}}$ and δ_{smt-1}, together with the log of market population (interacted with format), the proportions of the population who are black and Hispanic (interacted with format) and the number of out of market stations in market m in each format at t and $t-1$. These additional instruments help to identify the non-linear parameters as they should be correlated with the derivatives of δ.[17]

In addition to these quasi-differenced moment conditions, I use several additional sets of moments to aid estimation.

5.2.2 Demographic Differenced Moments

As explained in Section 2 I have demographic-specific station share data for 10 age-sex specific groups in Spring 2006 (females aged 12-24, females aged 25-34, females aged 35-49, females aged 50-64 and females aged 65 and above and the same age groups for males). I assume that demographics affect listener tastes for stations in different formats in an additively separable way so that, for example, the "mean utility" of station s for females aged 25-34 is

$$\delta_{smt}^{25-34,FEM} = \widetilde{X_{smt}}\beta + \xi_{smt} + F_{st}\beta^{F,25-34} + F_{st}\beta^{F,FEM} \quad (17)$$

where $\widetilde{X_{smt}}\beta + \xi_{smt}$ is the mean utility of station s as defined above and $\beta^{F,25-34}$ and $\beta^{F,FEM}$ reflect the format tastes of people aged 25-34 year olds and females relative to the excluded group (males aged 12-24). Therefore,

$$\delta_{smt}^{25-34,FEM} - \delta_{smt}^{12-24,MAL} = F_{st}\beta^{F,25-34} + F_{st}\beta^{F,FEM}$$

[16] To calculate predicted market shares for given values of the parameters I use 50 Halton draws of the random taste parameters for each of the 40 demographic groups. I then weight the shares calculated for each group depending on the group's share of the total population. This is possible because my demographic variables separate the population into discrete (age-group x sex x ethnicity/race) bins rather than by continuous variables such as income.

[17] When I do not use the forward simulation moments described below estimation is facilitated by conditioning out the linear parameters β as suggested by Nevo (2000), p. 534.

so that ξ_{smt} can be differenced out.

I use these within-station, between-demographic differences in station mean utilities to form an additional set of moment conditions. As ξ_{smt} has been differenced out it is necessary to introduce a non-structural error to allow estimation. For example I define $\omega_{smt}^{25-34,FEM}$ as

$$\omega_{smt}^{25-34,FEM} = \delta_{smt}^{25-34,FEM} - \delta_{smt}^{12-24,MAL} - F_{st}\beta^{F,25-34} - F_{st}\beta^{F,FEM} \tag{18}$$

and use the moment condition that

$$E[Z_{smt}^{d}\omega_{smt}^{d}(\theta)] = 0 \tag{19}$$

for demographic group d. One interpretation of the non-structural errors is that they reflect measurement error in the demographic-specific market shares. However, they will also reflect aspects of horizontal product differentiation which are not captured by the format classification. For example, Sports stations typically have more male listeners than News stations even though I include them in the same News/Talk/Sport format. Instruments Z_{smt}^{d} include dummies variables for each demographic group/format combination as well as measures of the proportion of blacks and Hispanics in the demographic group. Two further sets of moments also help to pin down ethnic/racial tastes.

5.2.3 Ethnic/Racial Time Spent Listening Moments

I match the predicted Time Spent Listening (TSL) by blacks and Hispanics to estimates reported on Arbitron's website for 137 ethnically-diverse markets in Fall 2004 by forming moments

$$\begin{aligned} E[Z_{mt}^{TSL,BLACK}(\widehat{TSL_{mt}^{BLACK}}(\theta) - TSL_{mt}^{BLACK})] &= 0 \\ E[Z_{mt}^{TSL,HISPANIC}(\widehat{TSL_{mt}^{HISPANIC}}(\theta) - TSL_{mt}^{HISPANIC})] &= 0 \end{aligned}$$

where $Z_{mt}^{TSL,BLACK}$ is a dummy variable equal to 1 if m is one of the market-quarters with TSL data for blacks.

5.2.4 National Average Ethnic/Racial Listening to Different Formats

I match the predicted proportion of listeners to each format who are black or Hispanic to the proportions reported by Arbitron in Spring 2003, 2004 and 2005.

$$\begin{aligned} E[Z_{mt}^{PROP}(\widehat{PROPORTION}_{ft}^{BLACK}(\theta) - PROPORTION_{ft}^{BLACK})] &= 0 \\ E[Z_{mt}^{PROP}(\widehat{PROPORTION}_{ft}^{HISPANIC}(\theta) - PROPORTION_{ft}^{HISPANIC})] &= 0 \end{aligned}$$

where $Z_{mt}^{PROP,DST}$ is a dummy equal to 1 where market m is one of the markets used by Arbitron in calculating these proportions. These moments are similar to the "micro-moments" suggested by Petrin (2002) and they are useful in pinning down the ethnic/racial taste parameters for different formats.

5.2.5 Forward Simulation Moments

The final set of moment conditions involve predicting station shares one quarter forward given the estimated parameters and observed format switches. As described in Section 3, format switchers experience small increases in listenership on average which are slightly more volatile than the changes in listenership experienced by stations which do not change format. As forward simulation is used in the second stage of estimation to estimate station expected payoffs from switching formats it is obviously desirable that the model can match the share changes seen in the data.

The moments used match the observed mean and variance of the change in share for switchers and non-switchers together with the covariance of the change in share and the station's share prior to the switch being made. Separate moment conditions are estimated for home market and out of market stations.

5.2.6 Objective Function

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

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

where W is a weighting matrix. I use the optimal (two-step) GMM procedure of 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 moments formed using the consistent parameter estimates from the first step.

5.3 First Stage: Estimation of Station Policy Functions

The demand estimation provides estimates of listener tastes for different formats and the observed and unobserved component of quality for each station. These estimates are used to estimate station policy functions, i.e., a station's policy rule for choosing its format as a function of the state variables. As shown by Hotz and Miller (1993), a station's policy rule assuming optimal behavior, can be calculated from estimates of the probabilities of making different format choices given the observed state variables.

I follow the much of the recent applied literature (e.g., Ryan (2006), Ryan and Tucker (2006), Beresteanu and Ellickson(2006)) in assuming that these probabilities can be adequately approximated using a discrete model (here a multinomial logit) where the explanatory variables are rich functions of the state variables.[18]

5.4 Second Stage: Estimation of the Payoff Parameters

The second step estimates the parameters of the payoff function (4), including switching costs. Given current state $\mathcal{S}$, realized payoff shocks ε_s and station policies ς the expected discounted payoffs of a

[18] This reduced-form approach to estimating policy functions potentially provides a way to try to model the multiple choices made by firms owning multiple stations and this will be investigated in future versions of the paper.

station s at time $t = 0$ in format f_{s0} choosing to be in format f_{s1} in the next quarter are

$$\sum_{d=1}^{D} p_{dm} l_{sd0}(\mathcal{S}_0) - I(f_{s0} \neq 0)\theta_2 - I(f_{s0} \neq f_{s1}, f_{s1} \neq 0)\theta_3$$

$$+E_{\varsigma_s, f_{s1}, \varsigma_{-s}} \left\{ \sum_{t=1}^{\infty} \beta^t \left(\sum_{d=1}^{D} p_m l_{sdt}(\mathcal{S}_t) - I(f_{st} \neq 0)\theta_2 - I(f_{st} \neq f_{st+1}, f_{s1} \neq 0)\theta_3 + \varepsilon_{st}(f_{st+1}) \right) \right\} + \varepsilon_{s0}(f_{s1}) \tag{20}$$

$$= \sum_{d=1}^{D} p_{dm} l_{sd0}(\mathcal{S}_0) + E_{\varsigma_s, f_{s1}, \varsigma_{-s}} \sum_{t=1}^{\infty} \beta^t \sum_{d=1}^{D} p_{dm} l_{sdt}(\mathcal{S}_t) - \left(I(f_{s0} \neq 0) + E_{\varsigma_s, f_{s1}, \varsigma_{-s}} \sum_{t=1}^{\infty} \beta^t I(f_{st} \neq 0) \right) \theta_2$$

$$- \left(I(f_{s0} \neq f_{s1}, f_{s1} \neq 0) + E_{\varsigma_s, f_{s1}, \varsigma_{-s}} \sum_{t=1}^{\infty} \beta^t I(f_{st} \neq f_{st+1}, f_{st+1} \neq 0) \right) \theta_3 + E_{\varsigma_s, f_{s1}, \varsigma_{-s}} \sum_{t=1}^{\infty} \beta^t \varepsilon_{st}(f_{st+1}) + \varepsilon_{s0}(f_{s1})$$

$$= \Pi_{s0}(\mathcal{S}_0, \varsigma, \theta_2, \theta_3, \sigma, f_{s1}) + \varepsilon_{s0}(f_{s1})$$

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 strategy ς_s in the future and all other stations will use their strategies ς_{-s} both for selecting their formats for the next period and in the future. σ (the scale parameter of the distribution of ε) enters as it effects the expected future values of the εs. A nice feature of (20) is that, given an assumed value for the discount factor β, it is linear in the parameters θ_2 and θ_3. The probability that format f_{s1} is chosen, given the assumption that ε is distributed extreme value with location parameter 0 and scale parameter σ is given by the logit-type formula

$$\Pr(f_{s1}|\mathcal{S}_0, \varsigma, \theta_2, \theta_3, \sigma) = \frac{\exp \frac{\Pi_{s0}(\mathcal{S}_0, \varsigma, \theta_2, \theta_3, \sigma, f_{s1})}{\sigma}}{\sum_k \exp \frac{\Pi_{s0}(\mathcal{S}_0, \varsigma, \theta_2, \theta_3, \sigma, f_{s1})}{\sigma}} \tag{21}$$

I estimate the parameters $(\theta_2, \theta_3, \sigma)$ by matching the probabilities implied by (21) to the probabilities implied by the station policy functions estimated in the first stage.[19] This requires consistent estimates of the components of Π_{s0} i.e., expected future revenues, expected future switches and expected future ε_{st}s given station policies. These components are calculated using a forward simulation

[19] There are several ways this second stage might be carried out. BBL suggest matching estimating station payoffs under stations' actual policies and alternative policies, and estimating the parameters using a set of inequalities similar to (8). An alternative would be simply to apply a maximum likelihood estimator to (21).

procedure (Hotz et al. (1994) and BBL).

I apply the forward simulation procedure to stations observed in Fall 2005. The procedure works in the following way where station s is the station under consideration and I am calculating the components of its payoffs when it chooses to be in format f_{s1} in the next period:

1. I record the listenership of station s in the current period and whether it is active;

2. I calculate the state-conditional format switching probabilities for every station other than s (including out of market stations which will depend on conditions in their home market) using the first stage estimates. I compare these probabilities to a set of random numbers drawn from a uniform [0,1] distribution to select a format for each of these stations for the next quarter; I assume that station s chooses format f_{s1} in the next quarter. I record whether s makes a format switch;

3. I allow station qualities and market demographics to evolve according to the stochastic processes estimated in the first stage using draws of random numbers from normal distributions;

4. given the new configuration of the state space I record s's listenership and whether it is active. These values are discounted and added to the values from step 1.

5. I calculate the state-conditional format switching probabilities for every station including s (including out of market stations which will depend on conditions in their home market) using the first stage estimates. I compare these probabilities to a set of random numbers drawn from a uniform [0,1] distribution to select a format for each station for the next quarter; for station s I record the discounted conditional expected value of its ε given its chosen switch and the parameters of its distribution. This conditional expectation is $\sigma(\gamma - \ln(\Pr(f_{st+1}|\varsigma, \mathcal{S}_t))$ where γ is Euler's constant and $\Pr(f_{st+1}|\varsigma_s, \mathcal{S}_t)$ is the probability that format f_{st+1} is chosen given s's policy.[20] I record whether s makes a format switch and discount appropriately.

[20] One can also, of course, implement this procedure by drawing a set of εs for each station, applying the policy rule implied by the state-conditional format choice probabilities to find the chosen format and then recording the value of the ε associated with the chosen format.

6. steps 3 to 5 are repeated for a large number of quarters until, because of discounting, the effect of considering an additional period has only a small effect on the components of future payoffs. I currently use 60 periods.

7. to reduce the simulation error in the estimates of the components of station payoffs, averages are taken over a large number of repetitions of steps 1 to 6. I currently use 100 simulations.

8. steps 1 to 7 are repeated for each format choice of station s. For each of the different format choices the same set of simulation draws are used.

6 Results

In this section I discuss some initial parameter estimates.

6.1 First Stage: Listener Demand

Table 6 presents a selection of the parameter estimates from the random coefficient logit model of listener demand.[21]

The demographic parameters show a pattern which is consistent with the average listener demographics reported in Table 1. For example, women like Rock and News programming less, on average, than men but prefer Religious programming. CHR/Top 40 is most valued by the youngest listeners, whereas News, Religious and Other Music are preferred by older listeners.

The format mean utilities need to be interpreted together with the standard deviations of the random coefficients. The formats with the lowest mean utilities are those with the largest standard deviations, so that even though mean utility is very low stations in those formats may still have many listeners because some listeners value their programming highly. For Religious and (maybe) Country programming this pattern of low mean but high variance utility is intuitively appealing. It is less

[21] The parameters which are not listed include a full set of time x format interactions which are almost all statistically insignificant and very small, and display slightly negative serial correlation. When I simulate the model forward I ignore the possibility that format-attractiveness evolves over time.

appealing for News programming, although this format does include Sports and Talk stations which some listeners may like or dislike intensely.

The AM x format interaction coefficients show the expected pattern, with AM yielding higher quality in the non-contemporary music formats.[22] The out of market x format interaction coefficients have to be interpreted carefully. On the one hand, out of market stations may not be received in the whole market and their programming may be less relevant to local listeners. On the other hand, there is also a selection effect which is not accounted for. Very small home market stations with too few listeners to be rated by Arbitron are included in estimation but the equivalent out of market stations are treated as not being in the choice set at all. As expected, increased signal coverage increases mean utility.

The least satisfactory demand parameters are probably the region x format interactions. The excluded region is East North Central (IL, WI, OH, IN, MI). While some of the parameters are sensible (Country is disliked in New England), other parameters do not: for example, Religious stations yield higher average utility in New England than East South Central (AL, KY, TN, MS). This potentially presents a problem for my exercise: New England has almost no Religious stations so, if the mean utility of a Religious station in New England is not very low, then a station that switches into Religious programming will face little competition and should gain a very large audience.

The quasi-differencing parameter ρ^{ξ} is 0.984, indicating that station quality is highly persistent from quarter-to-quarter. As part of the estimation, I also find the other parameters of the stochastic process governing quality evolution. A station's quality tends to decline when it changes formats. This is inspite of the average increase in station listenership when stations switch formats. This is possible because, on average, stations move to more attractive formats where there is less competition.

Two comments are also in order about the fit of the model. First, as described above, I introduce a non-structural error into the demographic differenced moments. One rationalization for this non-

[22] One might argue that the pattern is not quite right as the AM signal is less good than FM for music programming but not necessarily better for non-music programming. This may result from assuming a common coefficient on AM and FM signal coverage even though many AM signals cover much larger populations.

structural error is that it simply reflects random measurement/sampling error in the Arbitron market shares. For each format I have calculated an R^2-type figure for these examining what proportion of the differences in the mean utilities for each station for each age/sex group are explained by the age/sex group dummies. The results show a sensible pattern. For News, CHR/Top 40 and Other Music where there are strong age/sex differences in listenership the average R^2s for each demographic group are above 0.5 (for News 0.69). On the other hand, for Urban and Hispanic where there is a much weaker age-sex pattern the R^2 is much lower (0.16 and 0.07 respectively).

The second issue is how well the model is able to match what happens to listenership when stations switch formats. Figures 2 and 3 compare actual changes in share to those simulated by the model for switchers and non-switchers. I use one simulated observation for each station. The fit of the distributions for stations which stay in the same format is close. The fit for stations switching formats is less good. There are a few observations (mostly for switches to Urban or Country) where very large increases in share are predicted. This is hard to see in the diagram. For the median switching station the model actually predicts a very small decrease in share whereas there is a small increase in the data. The mean matches closely, because the model can choose μ_2 to match this moment.

Although the fit of the distributions is quite close the correlation between changes in share in the data and in the model is low. For switching stations, excluding the extreme tail of simulated observations, the correlation is 0.13. Of course, it is hard to know what is a good correlation as both the actual data and the simulated observations will reflect random outcomes to some extent.

The inability to predict what happens to a station's share when it makes a particular switch is a significant problem in practice. One feature of the model makes it a much more important problem here than in a standard entry-exit setting. In my model each station has 11 choices per period. Therefore, if the outcome of only one or two options is poorly predicted it may seem that stations are ignoring opportunities to gain listeners and that their switching decisions must therefore be driven largely by the εs.

6.2 First Stage: Station Policy Functions

Table 7 presents a selection of the coefficients from the multinomial logit estimates of station policy functions. The specification includes a set of format dummies (interacted with whether the format is the current format) and a set of switch-type dummies similar to those reported in Table 5.

The coefficients for a station's current format make sense. The station is more likely to stay in a format which the demand system estimates is more attractive in the region and in which it has higher station quality based on band/format and signal coverage. Higher unobserved quality also makes a station less likely to switch. It is less likely to stay when it faces more competitors, with higher shares, competitors of higher quality based on observable characteristics (coverage, band) or competitors with higher unobservable quality.

The coefficients for alternative formats are less significant, although a station is more likely to switch to a format where it has higher observable quality (this is just the band effect as signal coverage is the same across alternatives) and is less likely to move to a format where competitors have higher observable qualities. The small size of the region-format effect may reflect the unintuitive pattern of region coefficients from the demand system, as the related (market-format attractiveness) coefficient in Table 6 was statistically significant.

Most of the demographic coefficients have the expected signs, although the growth of the black population does not seem to affect entry and exit from the Religious and Urban formats which have largely black audiences. This is probably because there is relatively little variation in black growth rates across cities with significant black populations. This contrasts with the case of Hispanics where there is more variation.

6.3 Second Stage Estimates

[to be presented at seminar]

7 Conclusion

References

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

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

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

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

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

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

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

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

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

[10] 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

[11] 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

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

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

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

[15] 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

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

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

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

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

[20] 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

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

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

[23] 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

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

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

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

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

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

[29] 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

[30] 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

[31] 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

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

[33] 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

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

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

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

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

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

[39] 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

[40] 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

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

[42] 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

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

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

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

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

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

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

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

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

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

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

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

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

[55] 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

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

[57] 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

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

[59] 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

<u>Notes:</u> 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: Multinomial Logit Model of Format Switching

Characteristics of Current Format		
Predicted Format Share	31.377	(4.224)***
Current Total Share of Home Mkt Stations	-28.315	(3.386)***
Current Total share of Out of Mkt Stations	-20.285	(6.426)***
Station Current Characteristics		
Largest Station in Format	-0.010	(0.046)
Current Station Share	165.645	(7.556)***
Median Share of Station in Market	-56.994	14.517)***
Switched in Previous Two Quarters	-0.246	(0.053)***
Characteristics of Alternative Format		
Predicted Format Share	64.319	(3.731)***
Current Total Share of Home Mkt Stations	-26.909	(3.308)***
Current Total share of Out of Mkt Stations	-6.054	(5.564)
Ownership Effects		
Number of Stations Commonly Owned in Alternative Format in Same Market	0.219	(0.029)***
Number of Stations Commonly Owned in Current Format in Same Market	0.049	(0.027)*
Number of Stations Commonly Owned in Alternative Format in All Markets	0.009	(0.001)***
Number of Stations Commonly Owned in Current Format in All Markets	0.009	(0.001)***
Recent Ownership Switch	-0.381	(0.050)***
Switch type - AM station		
Contemporary Music to Contemporary Music	-6.454	(0.155)***
Contemporary Music to News/Other M/Religion	-4.241	(0.117)***
Contemporary Music to Spanish	-5.186	(0.202)***
Contemporary Music to Dark	-5.758	(0.277)***
Switch type - AM station continued		
Dark to Contemporary Music	-4.932	(0.208)***
Dark to News/Other M/Religion	-2.970	(0.135)***
Dark to Spanish	-3.962	(0.332)***
News/Other M/Religion to Contemporary Music	-7.054	(0.121)***
News/Other M/Religion to Dark	-6.370	(0.193)***
News/Other M/Religion to News/Other M/Religion	-5.087	(0.108)***
News/Other M/Religion to Spanish	-5.284	(0.127)***
Spanish to Contemporary Music	-7.748	(0.257)***
Spanish to News/Other M/Religion	-5.020	(0.136)***
Spanish to Dark	-6.796	(0.509)***
Switch type - FM station		
Contemporary Music to Contemporary Music	-5.075	(0.111)***
Contemporary Music to News/Other M/Religion	-5.948	(0.122)***
Contemporary Music to Spanish	-5.314	(0.137)***
Contemporary Music to Dark	-6.882	(0.256)***
Dark to Contemporary Music	-4.430	(0.100)***
Dark to News/Other M/Religion	-4.548	(0.154)***
Dark to Spanish	-4.698	(0.293)***
News/Other M/Religion to Contemporary Music	-5.381	(0.117)***
News/Other M/Religion to Dark	-6.176	(0.330)***
News/Other M/Religion to News/Other M/Religion	-5.855	(0.175)***
News/Other M/Religion to Spanish	-5.184	(0.190)***
Spanish to Contemporary Music	-6.134	(0.189)***
Spanish to News/Other M/Religion	-6.348	(0.281)***
Spanish to Dark	-6.098	(0.511)***

Observations	83,028
Log-likelihood	-21963.24
Log-likelihood with only dummy for switching format	-24243.21

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Listener Demand Estimates

Constant/Formats	**Dummies**	**Std Dev Random Coefficients**
Commercial Radio (constant)	-10.74	3.62
Adult Contemporary	-	*0.04*
Contemporary Hit Radio/Top 40	0.72	0.85
Country	-9.10	6.23
Oldies	0.32	*0.16*
Rock	1.20	1.43
Urban	-7.09	3.86
News/Talk/Sports	-6.39	4.73
Other Music	-3.07	2.51
Religion	-9.38	5.88
Spanish-language	-0.45	0.92

Format/Demographic Interactions	**25-34**	**35-49**	**50-64**	**65+**	**Fem**	**Black**	**Hisp**
Adult Contemporary	0.82	1.04	0.55	-0.23	0.43	-0.68	-0.60
Contemporary Hit Radio/Top 40	-0.21	-0.92	-2.04	-2.58	0.30	0.50	*0.10*
Country	1.04	1.17	0.96	0.87	0.28	-3.10	-2.91
Oldies	0.37	1.15	1.35	0.93	-0.11	-0.96	-0.33
Rock	0.43	0.50	-0.63	-1.85	-0.70	-2.04	-1.10
Urban	0.04	-0.49	-1.24	-2.18	*-0.03*	5.75	-0.69
News/Talk/Sports	1.94	2.58	2.73	3.84	-1.10	-0.96	-1.92
Other Music	0.69	1.48	1.65	2.44	*-0.02*	0.29	-1.10
Religion	0.77	1.37	1.10	1.09	0.51	1.46	-0.59
Spanish-language	0.48	0.25	*0.03*	0.07	*-0.05*	-2.29	4.33

Format/Region Interactions (East North Central excluded)	**ESC**	**MidAtl**	**Mount**	**NE**	**Pacific**	**SAtl**	**WNC**	**WSC**
Adult Contemporary	0.57	0.75	-0.26	0.34	0.39	0.57	*-0.37*	0.73
Contemporary Hit Radio/Top 40	0.82	0.26	1.29	0.38	0.47	*0.20*	1.09	-0.70
Country	1.38	*0.01*	*0.30*	-1.21	-1.51	-0.44	-0.58	*0.22*
Oldies	-0.60	0.08	-0.14	-0.28	-0.20	-0.19	-0.28	-0.37
Rock	*-0.17*	-0.37	-0.51	-0.69	-0.48	-0.55	-0.14	-0.82
Urban	-1.24	-1.35	1.38	-1.04	-0.50	-1.14	-0.55	-0.77
News/Talk/Sports	-2.07	-1.36	-0.69	-0.11	-0.25	-0.49	0.77	-1.06
Other Music	-0.49	-0.62	0.76	-1.70	-0.84	-0.71	-0.61	-1.33
Religion	-0.71	-0.07	2.07	*-0.31*	-0.55	*0.18*	1.33	1.15
Spanish-language	-0.04	-2.03	-1.21	-1.04	-1.79	-1.21	-0.51	-2.98

Station Characteristics	**Constant**	**AC**	**CHR**	**Country**	**Oldies**	**Rock**
Coverage (home stations)	1.099	-	-	-	-	-
AM interactions	-0.83	-	3.03	-1.38	*-0.46*	-1.45
Out of market interactions	0.22	-	-0.48	0.67	-0.59	*0.02*

	Urban	**News**	**O Mus**	**Relig**	**Span**
Coverage	-	-	-	-	-
AM interactions	-0.94	2.3	1.21	1.2	-0.02
Out of market interactions	0.98	1.70	*0.37*	*-0.16*	*-0.31*

Quality Transition	
ρ	0.984
μ_1 (remain in format)	*0.05*
η_1	0.05
μ_2 (switch formats)	-1.33
η_2	0.09

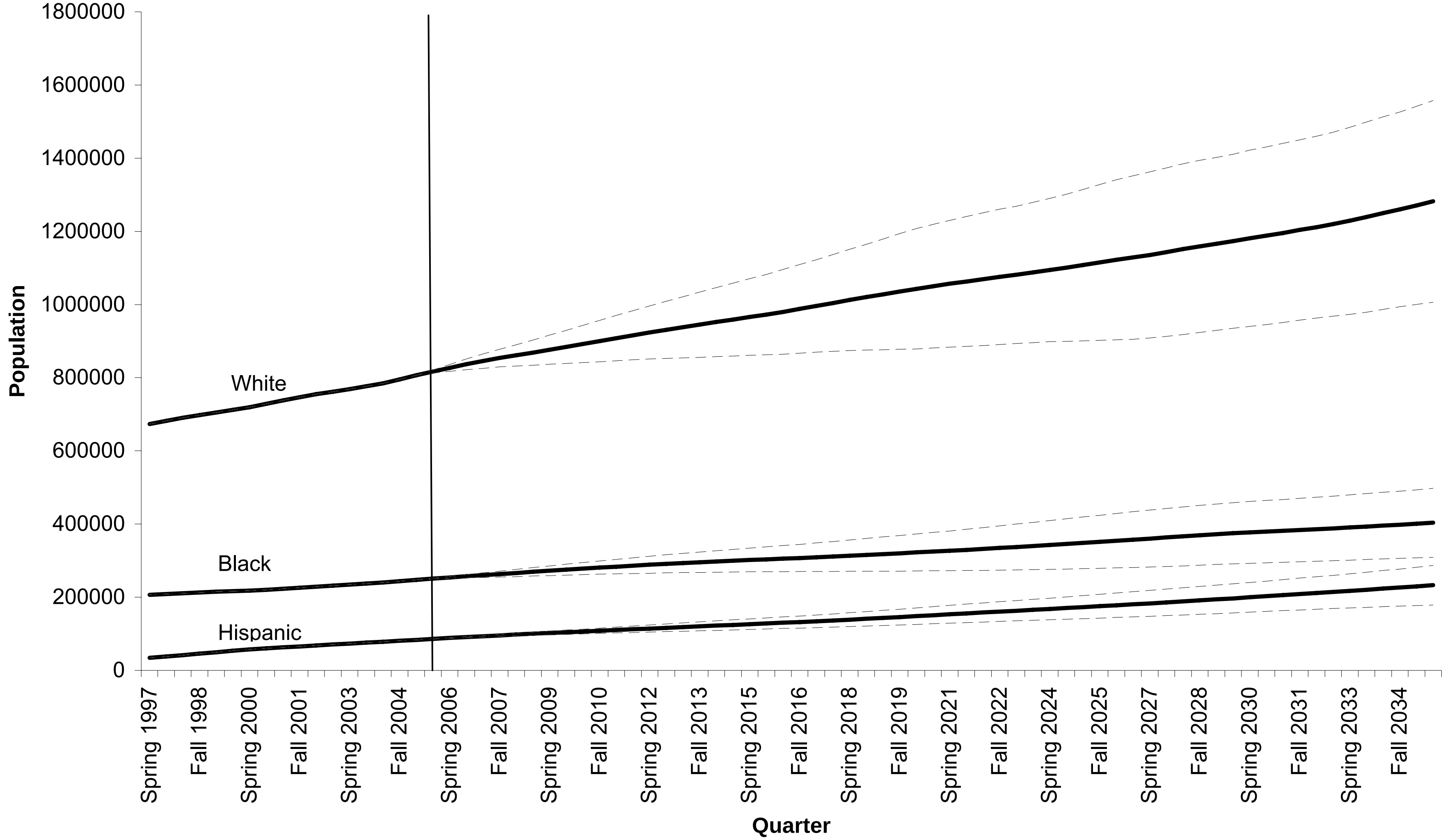
<u>Note:</u> time x format interactions included but coefficients not reported
coefficients in italics not significant at the 5% level

Table 7: Policy Function (Selected Parameters)

Current Format Characteristics		Alternative Format Characteristics	
Region-Format Effect	0.0897 (0.0342)***	Region-Format Effect	0.0356 (0.0333)
Observed Station-Format Quality ($X_{sfs}\beta_s$)	0.5594 (0.0484)***	Station-Format Quality ($X_{sfs}\beta_s$)	0.3905 (0.0466)***
Sum of Station-Format Qualities for other home market stations in format	-0.0356 (0.0082)***	Sum of Station-Format Qualities for other home market stations in format	-0.0516 (0.0083)***
Sum of Station-Format Qualities for out of market stations in format	-0.0246 (0.0078)***	Sum of Station-Format Qualities for out of market stations in format	-0.0159 (0.0062)***
Sum of Unobserved Station Qualities for other home market stations in format	-0.0242 (0.0031)***	Sum of Unobserved Station Qualities for other home market stations in format	-0.0001 (0.0028)
Sum of Unobserved Station Qualities for out of market stations in format	-0.0127 (0.0046)***	Sum of Unobserved Station Qualities for out of market stations in format	0.0031 (0.0041)
Number of other home market stations in format	-0.0804 (0.0140)***	Number of other home market stations in format	-0.0080 (0.0142)
Number of out of market stations in format	-0.0337 (0.0229)	Number of out of market stations in format	0.0369 (0.0212)*
Unobserved Station Quality ξ	0.1743 (0.0094)***		
Largest station in current format	0.4423 (0.0512)***		
Recent switch	-0.2957 (0.0540)***		
Ethnic/Race Interactions (only Urban, Religious and Spanish-language reported)			
Urban x Proportion of Pop Black	3.8841 (0.8058)***	Urban x Proportion of Pop Black	5.1689 (0.6137)***
Urban x Growth of Black Population	23.3747 (51.4167)	Urban x Growth of Black Population	-45.7194 (42.9997)
Religious x Proportion of Pop Black	-0.0278 (0.6418)	Religious x Proportion of Pop Black	4.9883 (0.6096)***
Religious x Growth of Black Population	57.7013 (46.9682)	Religious x Growth of Black Population	-26.6888 (42.6429)
Spanish-language x Proportion of Pop Hispanic	0.9078 (0.4517)**	Spanish-language x Proportion of Pop Hispanic	3.3305 (0.3923)***
Spanish-language x Growth of Hispanic Population	44.4288 (30.9826)	Spanish-language x Growth of Hispanic Population	132.2199 (19.2051)***
Observations	83,208		
Log-likelihood	-21,990.2		

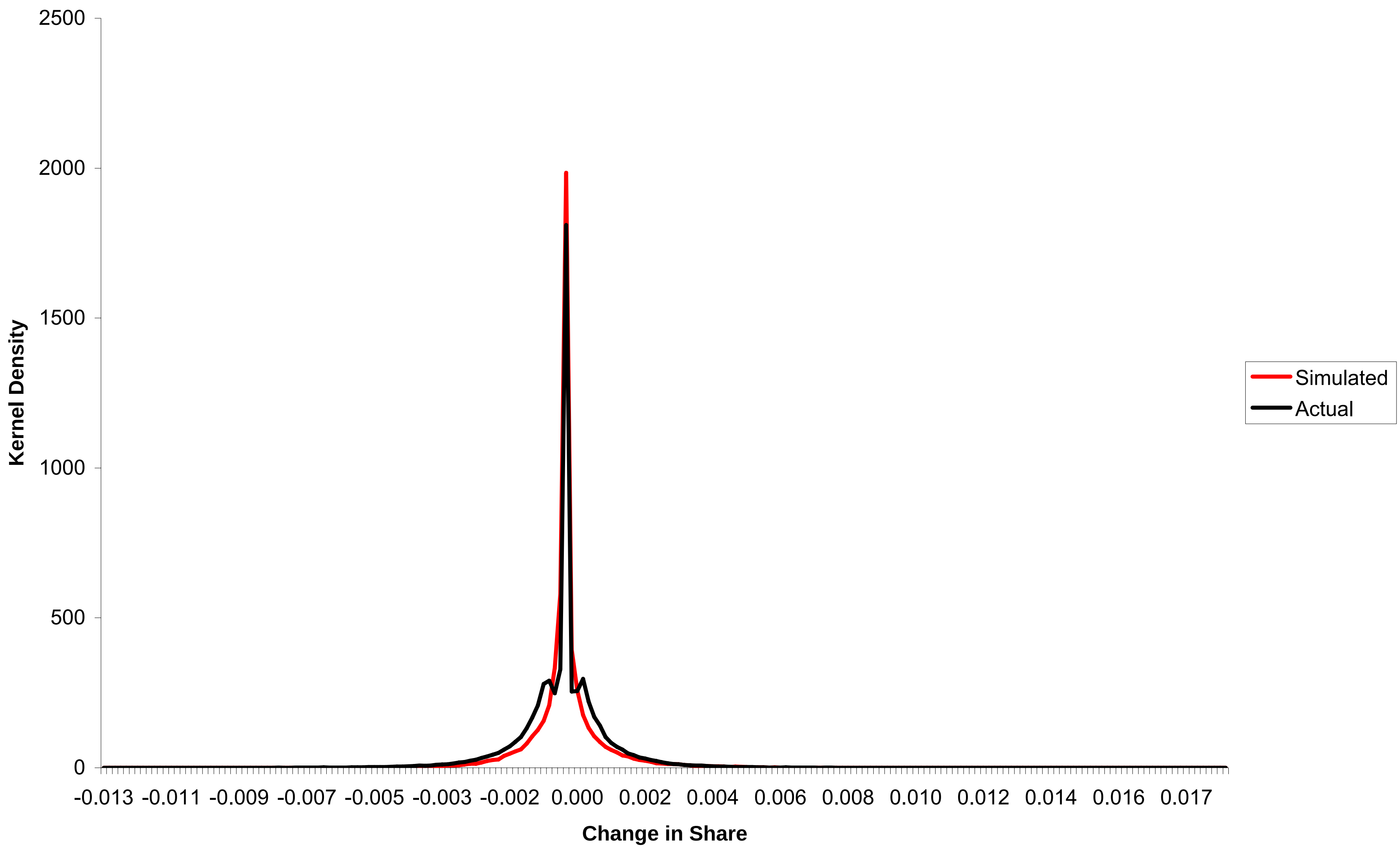
Note: specification also includes format dummies interacted with whether the format is the current format, ownership variables and switch-type dummies interacted with band (e.g., contemporary music to talk interacted with AM)
Standard errors in parentheses, not corrected for error from the demand system

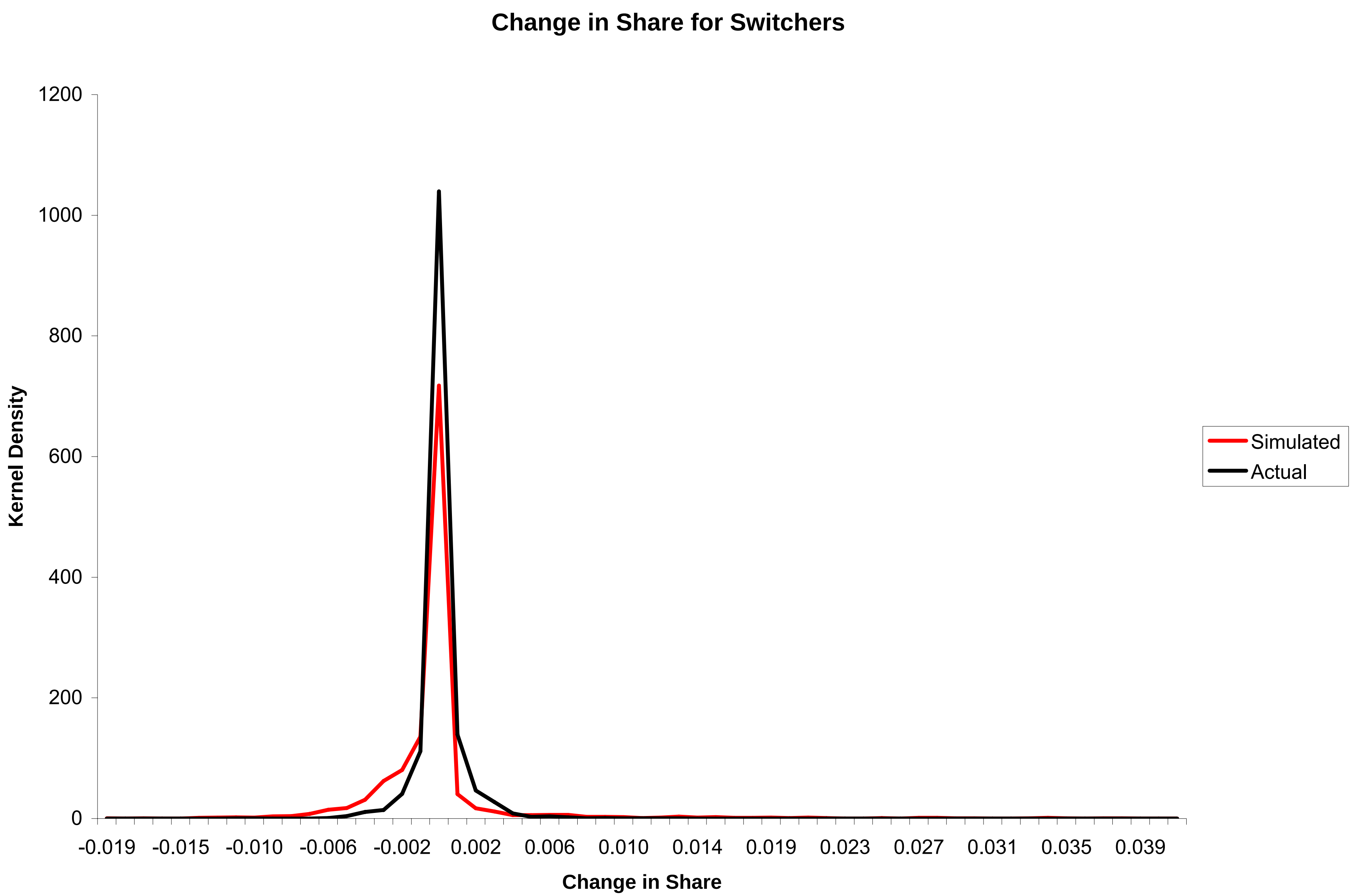
Figure 1: Evolution of Population of Non-Hispanic Whites, Non-Hispanic Blacks and Hispanics in Raleigh-Durham, NC from Fall 2005



Dotted lines represent one standard deviation around the mean

Change in Share for Stations Remaining in the Same Format




Change in Share for Switchers
Kernel Density
1200
1000
800
600
400
200
0
-0.019
-0.015
-0.010
-0.006
-0.002
0.002
0.006
0.010
0.014
0.019
0.023
0.027
0.031
0.035
0.039
Change in Share
Simulated
Actual