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DYNAMIC PRODUCT REPOSITIONING IN DIFFERENTIATED PRODUCT MARKETS: THE CASE OF FORMAT SWITCHING IN THE COMMERCIAL RADIO INDUSTRY

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ABSTRACT

The ability of firms to reposition their products can determine the effects of demand shocks, mergers and policy interventions in differentiated product markets. This paper estimates a dynamic oligopoly model to measure repositioning costs in the commercial radio industry. Based on a set of markets where industry revenues were around $88 billion, I find that stations may have spent as much as $6 billion on repositioning. However, repositioning costs are not large enough to prevent radio markets adapting quite quickly to demand shocks.

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1 Introduction

While there have been considerable advances in modelling consumer demand in differentiated product markets in the last 15 years (for example, Berry et al. (1995) and Hendel and Nevo (2006)), almost all analyses treat the set of available products as given. Yet in many industries the set of available products changes quite frequently and the ability of firms to alter their product offerings could substantially affect the outcomes of demand shocks or policy changes. For example, the medium-run effects of rising gas prices and environmental policies on the automobile industry will depend on how difficult and costly it is for American manufacturers to introduce more fuel efficient models (Berry et al. (1993)).

The potential for product repositioning already plays an important role in the analysis of horizontal mergers. In particular, the *Horizontal Merger Guidelines* recognize that if repositioning costs are small then the threat of repositioning by competitors may constrain market power even if demand-side substitution is limited (US Department of Justice (1997)). However, even though the potential for repositioning has been an issue in the analysis of mergers in industries as diverse as fountain pens, chewing tobacco, commercial radio and organic supermarkets, these analyses have taken place without any detailed study of how costly it is for firms to reposition their products in these types of industries.[1]

This paper fills this gap in the literature by estimating a dynamic oligopoly model to measure the costs associated with format switching in the broadcast radio industry. The basic structure of the model is as follows. In each period, a random coefficients demand model determines station audiences as a function of station formats, observed and unobserved station characteristics and local tastes, which depend on evolving market demographics. A revenue function translates audiences into revenues, allowing for listeners with different demographics to have different values to advertisers. Stations choose their formats to maximize expected future profits, recognizing how their choices may

[1] See the Department of Justice's Competitive Impact Statement in "United States vs. Clear Channel Communications, Inc. and AMFM, Inc." (http://www.justice.gov/atr/cases/f6900/6985.pdf), the District Court decisions "United States vs. Gillette Co." (828 F.Supp. 78) and "FTC v. Swedish Match et al." (131 F. Supp 2d 151) and the FTC complaint in "FTC vs. Whole Foods Inc. and Wild Oats Inc." (http://www.ftc.gov/os/caselist/0710114/070605complaint.pdf). Froeb et al. (2007) provide a theoretical analysis of repositioning after mergers, focusing on repositioning by the merging firms.

affect the future format choices of other stations.

The model allows for repositioning to be costly in three different ways. First, switching may reduce a station's quality, lowering its audience (quality effect). Second, it may cause revenues to fall, conditional on listenership, as the station searches for new advertisers (revenue effect). Third, there may be additional sunk expenditures associated with repositioning (sunk repositioning costs). These costs could arise from replacing staff, updating the station's programming library, hiring format consultants or additional marketing.

I estimate the model using a two-step approach. In the first step I estimate the demand model, the revenue function, station strategies and the transition processes for market demographics and station qualities. Assumptions on the timing of format choices allow me to estimate demand consistently even though format choices are endogenous. The first step provides estimates of the quality and revenue effects. In the second step I bound sunk repositioning costs using a moment inequality estimator.

I find that both the revenue effect and sunk repositioning costs are significant, but that there is no evidence of a significant quality effect as switching stations gain listeners even in the short-run. These qualitative results are broadly consistent with the Department of Justice's view of why format switching is costly.[2] My analysis also provides quantitative estimates. The revenue effect reduces station revenues by about 12% in the quarters immediately following a switch. The lower bound estimates of the additional sunk costs are of a roughly similar size. The upper bound estimates are larger, equal to about one year's revenue for the average switching station. The upper bound estimates imply that the sample stations spent over $6 billion on sunk repositioning costs compared with total revenues of $88 billion (at 2004 prices) between 1997 and 2006. The dollar value of repositioning costs increases with market revenues, suggesting that markets of different sizes may adjust just as quickly

[2] "And, 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." (Klein (1997))

to demand shocks or mergers.

I also estimate some of the effects of the repositioning that I observe in the sample. Repositioning raised Hispanic listening by over 20%, as stations entered Spanish-language formats in many markets. Black listening also increased as stations switched to Urban and Contemporary Hit Radio formats. When I simulate the model I also find that stations move quite quickly in response to changes in ethnic/racial demographics, an example of a relatively permanent demand shock. Repositioning reduced the listenership of older listeners as there was some exit from formats such as Variety, Big Band and Easy Listening.

I also estimate how format switching affected the revenues of switching and non-switching stations. While repositioning tended to increase the revenues of switching stations, the average effect on non-switchers was small as in most cases repositioning simply changed which stations faced the most competition.

The paper is unusual in focusing on product repositioning by incumbents rather than market entry by new firms. This focus makes sense in my industry where spectrum constraints and licensing restrictions make station entry and exit unusually rare. However, repositioning is also likely to be the more important margin of change in any industry with large scale and scope economies (such as automobiles) especially in the relatively short time horizons considered in many policy analyses.[3] For example, merger analysis asks whether entry or repositioning could constrain market power in a period of one to two years.

There are several features of the radio industry which make it an excellent place to study repositioning. The existence of discrete measures of positioning (formats) and the lack of technological barriers to repositioning provide a close fit to the model which I set out below. The local nature of the industry allows me to observe many examples of format switching even though the rate of switching is quite low. In addition, some of the most important drivers of repositioning, such as demographic changes, are observable and differ significantly across markets. Finally, the feasibility

[3] Bernard et al. (2006) show that changes in the products offered by existing firms account for much larger changes in output than firm entry and exit in most manufacturing industries.

of repositioning has been a substantive issue in the analysis of many radio stations mergers. My estimates of repositioning costs are therefore directly relevant to an on-going policy debate.

1.1 Relationship to the Existing Literature

1.1.1 Format Switching and Repositioning Costs

The substantive topic of the paper is related to a couple of other literatures. Berry and Waldfogel (2001) and Sweeting (2006) provide reduced-form analyses of how radio station ownership affects variety and listenership. Berry and Waldfogel (1999) find evidence of excess entry in the radio industry, in the sense of Mankiw and Whinston (1986), using a static entry model. Tyler Mooney (2006) uses a static structural model to show that during the late 1990s stations migrated to formats which were more valued by advertisers. Romeo and Dick (2005) show that stations gain listeners when they switch format.

While there has been no previous attempt to estimate the costs which firms have to pay to reposition their products in a horizontally differentiated industry, there have been several attempts to estimate the migration costs paid by individuals or households when moving between different cities (Kennan and Walker (2006), Bayer and Juessen (2006) and Gemici (2007)) offering different labor market opportunities. The firm setting is more complex in that it is necessary to model competitive interactions between firms. On the other hand, it may be easier to estimate the opportunities facing firms in different market niches than it is to estimate the labor market opportunities available to a particular household.

1.1.2 Estimation of Dynamic Oligopoly Models

A dynamic model is needed to estimate repositioning costs because the returns from repositioning are likely to be realized over a number of periods during which a market might evolve in many different ways. Several recent papers (Aguirregabiria and Mira (2007), Bajari et al. (2007), Berry et al. (2007) and Pesendorfer and Schmidt-Dengler (2003)) have proposed methodologies for estimating dynamic discrete choice games with Markov Perfect Nash Equilibria. Following Hotz and Miller (1993) and Hotz et al. (1994) in the single agent setting, these approaches avoid solving for equilibrium strategies at each step of the estimation process. The approach which I take is closest to the two-step procedure suggested by Bajari et al. (2007). In the second step, I use moment inequalities to estimate repositioning costs, using the methods proposed by Pakes et al. (2006). These methods have been used by Ho (2007) and Ishii (2005) to estimate models in static settings. Holmes (2007) uses these methods in a dynamic analysis of Wal-Mart's store location problem.

Ryan (2005), Collard-Wexler (2005), Beresteanu and Ellickson (2006) and Macieira (2006) have estimated dynamic oligopoly models using industry data. Ryan (2005) and Collard-Wexler (2005) examine entry and exit in the homogenous product cement and ready-mix concrete industries. Beresteanu and Ellickson (2006) and Macieira (2006) use logit demand models to allow for a simple form of vertical product differentiation in the supermarket and supercomputer industries. In the radio industry both horizontal product differentiation and vertical product differentiation are important and I use a rich random coefficients demand model to capture these effects.

The two-step estimation approach requires me to consistently estimate a model of listener demand in the first step allowing for format choices to be endogenous.[4] I achieve this by making assumptions on the timing of innovations in station quality relative to station format choices. This is similar to the way in which the structural productivity literature uses timing assumptions to address the endogeneity of input choices (Olley and Pakes (1996), Blundell and Bond (2000), Levinsohn and Petrin (2003), Ackerberg et al. (2005)).[5]

[4]The endogeneity problem could also be solved by estimating demand and product choice simultaneously, as attempted in the static setting by Crawford and Shum (2006) and Draganska et al. (2006). This type of approach would not be computationally feasible in a dynamic setting with a rich model of demand.

[5]Berry et al. (1995), p. 854, recognize that timing assumptions might be used in the demand context. Einav's (2007) approach to dealing with the endogeneity of movie release dates by assuming a particular process for the decay of a movie's appeal has a similar spirit.

1.2 Outline

The paper is structured as follows. Section 2 describes the data and Section 3 presents some stylized facts on format switching. Section 4 presents the model and Section 5 details the estimation procedure. The empirical results are presented in Section 6. Section 7 concludes.

2 Data

Data on station characteristics (formats, band, signal coverage etc.), station ownership and station ratings are taken from BIAfn's Media Access Pro database.[6] This database also includes BIAfn's estimates of station advertising revenues. I use data from the Spring and Fall quarters each year from Spring 1996 to Spring 2006, although 56 markets are missing share data for Fall 1996.[7] The database only contains ratings data for commercial stations, and only these stations are used in what follows.[8]

2.1 Formats

Table 1 lists the ten formats used to categorize each station's programming together with several measures of listener demographics.[9] These formats combine some of BIAfn's format categories, such as Rock and Album Oriented Rock, which are particularly similar. The "Other Music" format includes several format categories which appeal to older listeners. The structural model also includes a "Dark" format for stations which are off-air.

2.2 Geographic Markets and Demographic Data

Arbitron defines local radio markets for estimating station ratings. These markets are also used by the FCC and the Department of Justice. The stylized facts below are based on data from 274

[6] 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*.

[7] Smaller markets are only rated in the Spring and Fall quarters, so using data from only these quarters avoids having to deal with problems where markets are observed with different frequencies.

[8] I include market-format fixed effects in the demand specification which should control for the effect of non-commercial stations which remain in the same format and do not change quality over time.

[9] The format trends data reported on Arbitron's website indicates that there has been relatively little change in format demographics from 1998 to 2006.

Arbitron markets, excluding Puerto Rico, markets dropped by Arbitron prior to 2006 and markets added by Arbitron after 2001. Local market demographics (age, sex and ethnicity/race combinations) are measured using the US Census's Annual County Population Estimates aggregated to the market level.[10]

Some Arbitron radio markets are close enough that stations from several markets may compete for the same listeners. I include these markets when presenting several stylized facts about format switching but I exclude them when estimating the structural model to avoid modelling interactions between markets.

2.3 Station Listenership and Revenue Data

Arbitron reports quarterly estimates of station listenership based on diaries completed by a sample of listeners. I use the station's aggregate market share, where the market is the time available to the population aged 12 and above during a broadcast week of Monday-Sunday 6am-midnight.[11] As described in Section 5, I also use Arbitron data on the average demographics of listeners to each format in Arbitron's 100 largest markets. I use BIAfn's estimates of annual station revenues. These estimates are based on a combination of data reported by stations and a proprietary formula.

3 Format Switching: Some Stylized Facts

This section briefly describes several stylized facts about format switching and what happens to stations' listenership when they switch formats. I focus on those facts which are informative about repositioning costs and which motivate the structure of my model. The statistics are based on stations in their home markets.

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

[11] This share is calculated by multiplying the station's "AQH Share" (which measures its share of all radio-listening), reported by BIAfn, with the market's APR figure(which measures the proportion of people aged 12 and above listening to radio). The APR numbers come 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.

1. The switching rate is 4.2% per half-year and AM and FM Stations exhibit distinctive switching patterns. Table 2 shows the format-to-format switching matrices for AM and FM stations. On average, 4.2% of stations switch formats every half-year (the data comes from the Spring and Fall quarters) with 3,830 switches observed in the data. Switching patterns differ across bands. AM stations are more likely to switch to talk formats, such as News/Talk and Religious, consistent with the AM signal providing lower quality for music programming. This difference is potentially useful in revealing how sensitive switching behavior is to differences in expected revenues. FM stations switch more evenly across formats. In particular, FM stations are not systematically more likely to switch between different contemporary music formats (e.g., Country and Rock) than between these formats and non-music programming. This suggests that my format classification does identify different types of programming and that, as I assume below, the costs of switching between different pairs of formats are similar.[12]

2. Format switchers stations gain significant listenership. Figure 1 shows what happens, on average, to a station's share when it switches formats. Market shares are measured as the percentage of time spent listening to a station by people aged 12 and above during a broadcast week of Monday-Sunday 6 am-12 pm (the sum of market shares for all of the stations in market is typically around 13%). In the figure I normalize the station's share to be zero in the period (-1) immediately prior to the switch (the average switcher has a market share of 0.5%).[13] A station's share increases significantly in the two periods (one year) following a format switch and then levels off.

I focus on horizontal product repositioning as the way in which stations gain listeners/revenues, modelling the evolution of station quality in a simple way. Figure 2 provides some evidence that format switching *is* a major way in which stations gain listeners. The solid line shows the kernel density of

[12] The average changes in market share for stations making different kinds of switch are also not significantly different from one another. Of course, these patterns partly reflect the fact that my coarse format definitions exclude very small changes in programming (e.g., Soft Adult Contemporary to Lite Adult Contemporary) which are more common.

[13] The plotted points are coefficients from a station-fixed effects regressions including a full set of Arbitron quarter dummies and dummies for the quarters around a switch. Only stations observed for all of the quarters around the switch are included. Stations switching to and from the inactive format (Dark) are excluded.

changes in share over a two year period and the dashed line shows the proportion of stations in each share change bin which switched formats during the same two year period. The average proportion of stations changing format is 0.15, but this rises to over 0.5 for stations experiencing the largest share increases. The diagram also shows that relatively few format switchers lose significant share suggesting that they may face relatively little uncertainty about how they will perform in their new formats.

3. The rate of format switching is similar in markets of different sizes. If the dollar value of format switching costs is the same in every market then one would expect to observe less switching in smaller markets where stations have fewer listeners and lower revenues. One would also expect to see switching stations increasing their market shares by larger amounts in smaller markets. Figures 3(a) and (b) show that the rate of switching and the share gain of switchers is very similar across markets of different sizes, suggesting that repositioning costs must be smaller in smaller markets.

One can calculate a very rough estimate of the magnitude of repositioning costs using an estimate of the value of listeners gained following a format switch. For example, suppose that the marginal switcher expects its market share to permanently increase by 0.08 percentage points if it switches and that both the market population and the price per listener are fixed at their average 2004 values. Assuming an annual discount rate of 10%, Table 3 lists the present discounted value of this change in share in five markets. Of course, there are many things that this calculation ignores, such as the difference in the expectations of the marginal and the average switching station, the different value to advertisers of different groups of listeners and the many ways in which markets might evolve in the future. The structural model is designed to take these factors into account.

4. Changes in market demographics and competition affect format switching. My model explains format switching by competition for listeners and changes in market demographics, especially changes in their ethnic/racial composition. Table 4 shows coefficients from long-differenced IV regressions (Spring 1996 to Spring 2006 for those markets always followed by Arbitron) where the dependent variable is the proportion of local stations in a format and the explanatory variables include ethnic/racial demographics and the market share achieved by out of market stations as a measure of competition. This variable is potentially endogenous and I instrument for it as explained in the notes beneath the table.

The coefficients show the expected pattern. Increasing black (Hispanic) populations are associated with more Urban and Religious (Spanish) stations. Competition generally reduces the number of stations in a format and the coefficient is statistically significant when the formats are pooled together.

4 A Dynamic Model of the Radio Industry

This section describes the various components of the dynamic model of the radio industry.

4.1 State Space

The state space is composed of (i) a set of station, market and format characteristics which are observed by all stations when they make their format switching decisions and which are observed or can be estimated by the econometrician (denoted $\mathcal{S}$ in what follows), and (ii) a set of iid private information payoff "shocks" that affect a station's payoff from making each format choice for the next period.

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): those listed in Table 1 and a "Dark" format (0) for inactive stations. Each station has several observed quality characteristics which are assumed to be fixed over time: band, signal coverage, transmitter power, year first on air and out of market status. The quality of AM stations is also allowed to vary by format. Each station also has a quality component ξ_{smt} which can evolve over time. This is not directly observed in the data but I assume that it can be estimated.

Treating the number of stations as fixed is a simplification, but it is a reasonable first approximation in this industry. Entry is severely limited by both spectrum constraints, especially in larger markets and in densely-populated regions of the country, and by the FCC's licensing process. As a result there are only 290 examples of new entry during the sample period, compared with 4,739 stations active in 1996. There were also less than 50 examples of exit and many of these were due to the FCC withdrawing the station's license.[14] I assume that entrants and exiters are in the Dark format when they are not active.

4.1.2 Market Characteristics

The population in each market is made up of 18 mutually exclusive age-gender-ethnic/race groups (3 age x 2 gender x 3 ethnic/racial). Age-gender mixes differ relatively little within markets over time and I only model the growth of the three ethnic/racial groups (non-Hispanic whites, non-Hispanic blacks and Hispanics), assuming that the same growth rate applies to each of the relevant age-gender groups. Each market is also associated with a particular advertising price per listener and each format in each market has a particular attractiveness to listeners $(\overline{\gamma_m^F})$ which is assumed to be fixed over time and which can be estimated.

4.2 Timing

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

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

2. listeners choose which station to listen to based on current station qualities, formats and the attractiveness of each format. Station listenership is translated into revenues by a function

[14] These counts of entry and exit exclude cases of a construction licence being granted but the being relinquished without the station ever going on-air. The entry count also does not include stations which start being rated by Arbitron during the sample period because they gain enough listeners to start meeting Arbitron's Minimum Reporting Standard (about 0.3% of radio listening). The analysis in Berry and Waldfogel (2001) would include these examples as cases of station entry.

capturing the operation of the advertising market. Active stations incur a fixed cost;

3. each station observes additive random shocks (ε^F) 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 ε^Fs, each station simultaneously chooses a format for the next period. Station payoffs (advertising revenues, fixed costs, repositioning costs, ε^F) for the current period are realized; and,

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

4.3 Static Station Payoffs

A station's payoff in a period depends on its listenership, which is translated into dollars by a revenue function, a fixed cost and its format switching choice. Formally, the payoff for station s in market m and format f_{st} in quarter t which chooses f_{st+1} for the next quarter is

$$\pi_{smt}(f, \mathcal{S}, \varepsilon_{st}, \alpha, \theta, \sigma) = R(L_{smt}(\mathcal{S}, \Gamma), \alpha) - \theta_1 I(f_{st+1} \neq f_{st}, f_{st+1} \neq 0) \\ - \theta_2 I(f_{st} \neq 0) + \sigma \varepsilon_{st}^F(f_{st+1})$$

L and R are the functions determining listenerhip and revenues. The parameter θ_1 is the sunk repositioning cost paid when a station switches to a different active format and θ_2 is a per-period fixed cost paid when a station is on-air (not Dark). σ scales the iid payoff shocks (ε_{st}^F) which are assumed to be drawn from a Type I extreme value (Gumbel) distribution with location parameter 0. Differences in the ε^Fs can be interpreted as reflecting heterogeneity in format repositioning costs and I use this interpretation in Section 6.

4.3.1 Listener Demand ($L_{smt}(\mathcal{S}, \Gamma)$)

Listener demand is determined through a static, discrete choice, random coefficients logit model. The market is defined as the time available to people aged 12 and above. Each listener chooses at most one station. The utility listener i in market m receives by choosing station s in quarter t is

$$u_{ismt} = \gamma_i^C + F_{smt}\gamma_{imt}^F + X_{sf_st}\gamma^S + \xi_{smt} + \nu_{ist}^L \tag{1}$$

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

$$\gamma_{imt}^F = \overline{\gamma_m^F} + \gamma_A^F A_i + \gamma_E^F E_i + \gamma_G^F G_i + \Gamma_{RC}^F v_i^F \tag{2}$$

$\overline{\gamma_m^F}$ is a vector of market-format fixed effects which allows tastes to vary across markets and controls for the presence of significant non-commercial competitors in some market-formats. γ_A^F, γ_E^F and γ_S^F allow additively separable effects of age, ethnicity/race and gender on format preferences. The v_i^Fs are assumed to be drawn from a standard normal distribution and allow for individuals to have systematic preferences for stations in the same format in addition to those due to demographics. As is standard in most of the literature, Γ_{RC}^F is assumed to be diagonal. X_{sf_s} are observed characteristics of station s, such as signal coverage, as well as a full set of AM band-format interactions. ξ_{smt} is the unobserved component of station quality. It is assumed that all listeners value ξ_{smt} and the observed X_{sf_s} characteristics in the same way.

4.3.2 Revenue Function, $R(L, \alpha)$

The revenue function is used to translate listenership into dollars of revenue. In the simplest specification, I assume that station s in market m in quarter t receives revenues R_{smdt} when it is chosen by a listener with demographics d

$$R_{smdt} = \alpha_{my(t)}(1 + W_{smt}\alpha^W)(1 + D_d\alpha^D) + \varepsilon^R_{smt} \tag{3}$$

$\alpha_{my(t)}$ are a full set of market-year fixed effects which capture differences in advertiser demand that are common across all stations in a market. I use market-year fixed effects as revenues are reported on an annual, rather than quarterly, basis. W captures additional station characteristics. In particular, I allow per listener revenues to vary with the degree of competition that the station faces in its format and whether the station is commonly owned. I also allow an additional effect of a recent format switch on revenues, as format-switchers may have to lower advertising prices or carry fewer commercials while they develop new relationships with advertisers.

4.4 Evolution of the State Space

Three parts of the state space evolve over time: station formats, unobserved station qualities and market ethnic/racial demographics. Station formats evolve deterministically with station choices.

4.4.1 Unobserved Station Quality

I assume that unobserved station quality evolves according to

$$\xi_{smt} = \rho^\xi_1 \xi_{smt-1} + \mu^\xi_t + \nu^\xi_{1smt} \tag{4}$$

for stations remaining in the same format where ν_{1smt} are iid innovations in quality drawn from some distribution. The μ^ξ_ts are time fixed effects. I assume that quality evolves according to

$$\xi_{smt} = \rho^\xi_2 \xi_{smt-1} + \mu^\xi_t + \mu^\xi_2 + \nu^\xi_{2smt} \tag{5}$$

for stations switching formats. This second transition process applies only between the periods when the format switch takes place.

4.4.2 Market Demographics

I assume that the growth rate of each ethnic/racial group e also follows a stationary AR(1) process

$$g_{emt}^{D} = \rho^{D} g_{emt-1}^{D} + \mu^{D} + \nu_{emt}^{D} \tag{6}$$

where $\nu_{emt}^{D} \sim N(0, \eta^{e})$. I assume that the parameters are the same for all ethnic/racial groups, but with a high value of ρ^{D}, the current rapid growth of Hispanic populations in many markets tends to persist for some years into the future.

4.4.3 Repositioning Costs

The model allows for three different types of repositioning cost. First, a station's quality may fall when it switches formats causing it to lose listeners (μ_2^{ξ}). Second, a station may receive lower revenues, for given listenership, following a format switch as it searches for new advertisers ($W_{smt}\alpha^{W}$). Third, a station may have to pay additional sunk costs when switching (θ_1). These costs could result from hiring format consultants, marketing the station, replacing staff or making investments in programming that have not been explicitly modelled.

4.5 Equilibrium Concept: Markov-Perfect Nash Equilibrium

In common with the literature, I assume that stations play a symmetric, anonymous, stationary, pure strategy Markov Perfect Nash Equilibrium.[15] Formally, a station's Markov Perfect strategy ς_s is a function mapping from the current observable state space ($\mathcal{S}$) and the station's own current payoff

[15] This involves making an assumption that this type of equilibrium exists as well as which equilibrium is played if there are several. Dorazelski and Satterthwaite (2003) examine the existence of Markov Perfect Nash equilibria in dynamic oligopoly models. One obvious difference between my model and the stylized model that they consider is that I have continuous rather than discrete state variables, but one could convert my state variables into discrete ones by considering an arbitrarily fine discretization.

shocks (the ε_s^Fs) to actions (format choices), i.e., $\varsigma_s : \mathcal{S}$ x $\varepsilon_s^F \rightarrow A_s$.

Station s's value function prior to the realization of its current ε_s^Fs is

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

where β is the common discount factor, $\pi_s(\mathcal{S}, \varsigma_s(\mathcal{S}, \varepsilon_s^F))$ are its static payoffs as a function of the state variables and its own strategy and $P(\mathcal{S}'|\varsigma(\mathcal{S}, \varepsilon^F), \mathcal{S})$ is the probability that the state in the next quarter will be $\mathcal{S}'$ given current state $\mathcal{S}$ and the strategy profiles of all stations 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

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

Prior to the realization of the ε_s^Fs a station's optimal strategy implies a probability distribution over format choices. A profile of strategies ς^* is a Markov Perfect Nash Equilibrium if each station's strategy is optimal given the strategies of other stations.

An important simplifying assumption is that stations are treated as entities maximizing their individual payoffs, even though many stations are commonly owned and there was increasing common ownership during the sample period. Common ownership could affect format choices because owners want to avoid audience cannibalization, desire to exercise market power over listeners or advertisers or exploit economies of scope by offering similar kinds of programming on different stations. It is beyond the scope of the current paper to include the effects of common ownership in the dynamic model. Instead I attempt to control for the effects of common ownership on station revenues and station policies, and then estimate repositioning costs treating stations as individual payoff-maximizing firms.

5 Estimation

5.1 Road Map

I follow most of the recent literature by estimating the model using a two-step approach. Listener demand, station strategies, the revenue function and transition processes of the state variables are estimated in the first step. In the second step the remaining parameters of the payoff function (θ_1, θ_2 and σ) are estimated. This involves using forward simulation to calculate future station payoffs and then finding the parameters which make the observed policies optimal. I follow standard practice in assuming, rather than estimating, the value of the discount factor ($\beta = 0.95$).

5.2 First Step: Listener Demand and Station Quality Transitions

I estimate the parameters of the demand model and the transition processes governing unobserved station quality using a GMM procedure. My assumptions on the timing of format choices and innovations in quality allow for consistent estimation of these parameters even though format choices are endogenous.

5.2.1 Quasi-Differenced Demand Moments

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

$$\delta_{smt} = F_{smt}\overline{\gamma_m^F} + X_{sf_s}\gamma^S + \xi_{smt} = \widetilde{X_{smt}}\Gamma^L + \xi_{smt} \tag{9}$$

where Γ^L are the linear demand parameters. An endogeneity problem arises if unobservable qualities ξ_{smt} are correlated with local format tastes. A correlation would exist if, for example, higher quality stations tend to select into formats which are more popular (e.g., Country might be a more attractive format for a high quality station in Knoxville, TN than Boston, MA).[16]

[16] In my setting it is important to distinguish between the role of format and station quality in explaining station listenership. For example, if there is high listening to Country in Knoxville only because Country is popular in Knoxville then other stations may want to switch into Country. On the other hand, if Country listening is high because the stations in Country are of high quality then other stations would have less incentive to enter the format.

My assumptions on the timing of innovations in station quality allow me to overcome the endogeneity problem. Specifically I assume that the innovation in unobserved quality between period t and $t+1$ is only realized after the format choice for period $t+1$ is made. This allows me to form moments based on the innovations in quality.

For a station remaining in the same format

$$\xi_{smt} = \rho_1^{\xi}\xi_{smt-1} + \mu_t^{\xi} + \nu_{1smt}^{\xi} \tag{10}$$

so that the innovation in quality can be found by taking quasi-differences

$$\nu_{1smt} = \xi_{smt} - \rho_1^{\xi}\xi_{smt-1} - \mu_t^{\xi} \tag{11}$$

$$= (\delta_{smt} - \rho_1^{\xi}\delta_{smt-1}) - \left(\widetilde{X_{smt}} - \rho_1^{\xi}\widetilde{X_{smt-1}}\right)\Gamma^L - \mu_t^{\xi} \tag{12}$$

A similar quasi-difference gives the innovation in quality for format switchers

$$\nu_{2smt} = \xi_{smt} - \rho_2^{\xi}\xi_{smt-1} - \mu_2^{\xi} - \mu_t^{\xi} \tag{13}$$

$$= (\delta_{smt} - \rho_2^{\xi}\delta_{smt-1}) - \left(\widetilde{X_{smt}} - \rho_2^{\xi}\widetilde{X_{smt-1}}\right)\Gamma^L - \mu_2^{\xi} - \mu_t^{\xi} \tag{14}$$

The innovations can be used to form moment conditions

$$E[Z_{smt}\nu_{smt}(\Gamma, \rho^{\xi})] = 0 \tag{15}$$

where the Zs are instruments. Under my assumptions, all of the observed station characteristics, including formats at t and $t-1$, are valid instruments. The inclusion of both $\widetilde{X_{smt}}$ and $\widetilde{X_{smt-1}}$ as instruments results in a large degree of overidentification as the Γ^L parameters on them are restricted to be the same. Additional instruments, based on format x demographic and competition interactions, help to identify the non-linear taste parameters.[17] I also include the log of the $t-1$ market share interacted with an indicator for whether the station changes formats to help identify the ρ^{ξ}s.

Mechanically the calculation of these moments works as follows. First, the contraction mapping procedure of Berry et al (1995) is used to calculate the mean utilities given the current value of the non-linear taste parameters.[18] Second, given values of the ρ^{ξ} parameters, which are included in the set of non-linear parameters, the value of the linear demand parameters (which include all of the market-format fixed effects) can be found using the first-order conditions for minimizing the GMM objective function defined below as suggested by Nevo (2000).[19] Finally, the innovations are calculated and these are used to form the sample moments.

5.2.2 Additional Demographic Moments

As illustrated by Petrin (2002) additional information is useful in estimating the non-linear taste parameters. I add two sets of moments. The first set match the proportion of a station's audience in five age, gender or ethnic groups (females, 12-24, 25-49, blacks and Hispanics) with those reported for each format by Arbitron in its *Radio Today* publications for Spring 2003, 2004 and 2005. The numbers reported by Arbitron are averages for stations in the format across the largest 100 markets.[20,21] The moments are

$$E[Z_{dsfmt}(\widehat{P_{dsfmt}(\Gamma)} - P_{dft})] = 0 \tag{16}$$

[17] Specifically I include period t and $t-1$ format interactions with the number of other AM stations in the format, the number of other FM stations in the format and the sum of the proportion of market covered by the signals of other stations in the format. I also include the period t values for the proportion of blacks and Hispanics in the market population interacted with format dummies. This gives a total of 80 additional instruments.

[18] I use 50 Halton draws for each of the 18 demographic groups in each market-quarter (900 overall) and then calculate market shares by weighting each demographic group appropriately. I also use independent draws across market-quarters, which is appropriate as the Arbitron ratings panel varies across from quarter-to-quarter.

[19] This is possible because the additional moments I define below only depend on the δs and the value of the non-linear taste parameters.

[20] I also have age and gender-specific share data on listenership to individual stations in Spring 2006. I do not use this data because shares are not reported when they are too small, introducing a selection problem into the demand estimation. However, the shares for larger stations, where less data is missing is similar to the averages that I use, and the demand coefficients are similar using the station-specific share data and ignoring the selection problem.

[21] For blacks and Hispanics the numbers are calculated using the subset of markets where Arbitron tracks ethnic and racial listening.

where Z_{dsfmt} is an indicator equal to one if station-quarter st is in format f and in a market m used by Arbitron in calculating its reported proportions.

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

$$E[Z_{emt}(\widehat{TSL_{emt}}(\Gamma) - TSL_{emt})] = 0 \tag{17}$$

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

5.2.3 Objective Function

The moments are stacked into a vector $G(\Gamma, \rho^{\xi})$. The objective function is

$$\min_{\Gamma, \rho^{\xi}} G(\Gamma, \rho^{\xi})' W G(\Gamma, \rho^{\xi}) \tag{18}$$

where W is a weighting matrix. Following Hansen (1982) I use a two-step procedure where W is the identity matrix in the first step and the inverse of the covariance matrix of the moments calculated at the first step parameter values in the second step. Analytic derivatives are used to speed the search.

5.3 First Step: Revenue Function

The revenue function is estimated using BIAfn's estimates of annual station revenues and the predictions of demographic-specific station listenership from the estimated listener demand model. The empirical specification uses average revenues per listener as the dependent variable and allows for the fact that years (y) contain more than one period.[22]

$$R_{smy} = \frac{\sum_{t \in y} \alpha_{my}(1 + W_{smt}\alpha^{W}) \sum_{d=1}^{D}(1 + D_d \alpha^{D}) L_{sdt}(\mathcal{S}, \Gamma)}{\sum_{t \in y} \sum_{d=1}^{D} L_{sdt}(\mathcal{S}, \Gamma)} + \nu_{smy}^{R} \tag{19}$$

[22] I use average revenues per listener as the dependent variable as these are similar across markets of different sizes, whereas total revenues are much larger in larger markets.

The additively separable error does not have a structural interpretation - one might think of it as measurement error in BIAfn's estimates - and the function is estimated by non-linear least squares.[23]

5.4 First Step: Station Policy Functions

Stations' equilibrium strategies can be inferred from the probabilities that they make different format choices conditional on the observed state variables. In an ideal world these probabilities would be estimated non-parametrically. However, despite the large amount of data available, the size of the state space makes a non-parametric approach infeasible. I therefore assume that the choice probabilities can be adequately approximated using a multinomial logit model where the explanatory variables are functions of the state variables as well as controls for the effects of ownership. This approach is also used by Ryan (2005), Ryan and Tucker (2006) and Beresteanu and Ellickson (2006) and it has the advantage that the plausibility of the coefficient estimates can easily be verified.

Both the multinomial format choice model and the revenue function have estimates from the demand model as explanatory variables. It is not feasible to estimate all of these models simultaneously but I calculate corrected standard errors by expressing the first order conditions of the non-linear least squares and maximum likelihood estimators as moment conditions and applying the two-step estimator cited in Ho (2006).

5.5 First Step: Demographic Transitions

The process controlling the growth of ethnic/racial populations is estimated using the County Population Estimates. To prevent changes in very small population groups having an excessive effect on the estimates, I only use observations on those groups with at least a 5% share of market population.

[23] The key assumption is that format choices are not made in anticipation of future shocks to per listener revenues which might differ across formats.

5.6 Second Step: Estimation of Sunk Repositioning Costs

The parameters θ_1 (mean sunk repositioning costs), θ_2 (fixed costs of being on-air) and σ (the scaling parameter of the ε^Fs/heterogeneity of sunk costs) are estimated in the second step using a moment inequality estimator.

5.6.1 Estimating the Value Function

The inequalities are formed using the necessary equilibrium condition that a station's actual strategy yields higher expected payoffs than any alternative strategy

$$V_s(\mathcal{S}|\varsigma_s^*, \varsigma_{-s}^*, \theta, \sigma) - V_s(\mathcal{S}|\varsigma_s', \varsigma_{-s}^*, \theta, \sigma) \geq 0 \ \forall \varsigma_s' \tag{20}$$

$V_s(\mathcal{S}|\varsigma_s, \varsigma_{-s}^*, \theta)$ is a linear-in-parameters value function with four components representing the value of expected future revenues, fixed costs, switching costs and εs given strategies and future transitions of the state variables

$$V_s(\mathcal{S}|\varsigma_s, \varsigma_{-s}^*, \theta, \sigma) = \mathbf{R}_{s,\varsigma_s,\varsigma_{-s}^*} - \theta_1 \mathbf{S}_{s,\varsigma_s,\varsigma_{-s}^*} - \theta_2 \mathbf{F}_{s,\varsigma_s,\varsigma_{-s}^*} + \sigma \boldsymbol{\varepsilon}^F_{s,\varsigma_s,\varsigma_{-s}^*} \tag{21}$$

$$\text{where } \mathbf{R}_{s,\varsigma_s,\varsigma_{-s}^*} = E_{\mathcal{S},\varsigma_s,\varsigma_{-s}^*} \sum_{t=0}^{\infty} \beta^t R(L_{smt}(\mathcal{S}, \Gamma), \alpha),\ \mathbf{S}_{s,\varsigma_s,\varsigma_{-s}^*} = E_{\mathcal{S},\varsigma_s,\varsigma_{-s}^*} \sum_{t=0}^{\infty} \beta^t I(f_{st} \neq f_{st+1}, f_{st+1} \neq 0)$$

$$\mathbf{F}_{s,\varsigma_s,\varsigma_{-s}^*} = E_{\mathcal{S},\varsigma_s,\varsigma_{-s}^*} \sum_{t=0}^{\infty} \beta^t I(f_{st} \neq 0),\ \boldsymbol{\varepsilon}^F_{s,\varsigma_s,\varsigma_{-s}^*} = E_{\mathcal{S},\varsigma_s,\varsigma_{-s}^*} \sum_{t=0}^{\infty} \beta^t \varepsilon^F_{st}(f_{st+1})$$

and expectations are taken with respect to future transitions of the state variables given strategies. Bajari et al. (2007) describe how to formulate unbiased estimates of $\mathbf{R}$, $\mathbf{S}$, $\mathbf{F}$, $\boldsymbol{\varepsilon}^F$ using forward simulation. Appendix A describes my forward simulation procedure in detail. The logit assumption allows the expected value of $\varepsilon^F_{st}(f_{st+1})$ to be calculated analytically using the choice probabilities. $\mathbf{R}$, $\mathbf{S}$, $\mathbf{F}$, $\boldsymbol{\varepsilon}^F$ are calculated for a station's actual strategy and a set of alternative strategies which I describe below.

5.6.2 Pakes et al. (2006)

Given estimates of the value function, several estimators could be used to estimate the parameters. I choose Pakes et al. (2006)'s moment inequality estimator because it can provide consistent estimates even when there is simulation error in the estimated value function. Allowing for simulation error is important as it is prohibitively expensive to do enough simulations to effectively eliminate the simulation error from each observation.[24]

General Pakes et al. (2006) formulation. Pakes et al. (2006) consider estimating parameters using the necessary condition that a firm s's expected profits from using its actual strategy (or, depending on the setting, using its chosen action) ς_s^* are greater than under any alternative ς_s'

$$E[\pi(\varsigma_s^*, \varsigma_{-s}^*, x) - \pi(\varsigma_s', \varsigma_{-s}^*, x)|\mathcal{I}_s] \geq 0 \tag{22}$$

where x are variables affecting profits and $\mathcal{I}_s$ is firm s's information set at the time it chooses its strategy.

The researcher is assumed to have an estimate of $\pi(\varsigma_s, \varsigma_{-s}^*, x)$, $r(\varsigma_s, \varsigma_{-s}^*, x^0; \theta)$, where x^0 are variables observed by the econometrician and θ are parameters. They define two sources of difference between π and r, ν_{1,s,ς_s} and ν_{2,s,ς_s}

$$\pi(\varsigma_s, \varsigma_{-s}^*, x) = r(\varsigma_s, \varsigma_{-s}^*, x^0; \theta) + \nu_{1,s,\varsigma_s} + \nu_{2,s,\varsigma_s} \tag{23}$$

ν_{1,s,ς_s} is assumed to have an unconditional mean of zero, to be independent of $\mathcal{I}_s$ and not to affect s's choice of strategy. ν_{1,s,ς_s} can include the econometrician's error in measuring profits. On the other hand ν_{2,s,ς_s} is known by the firm and potentially affects its choice of strategy.

[24] Simulations are computationally costly because a random coefficients demand model and multinomial choice problems for as many as 50 stations have to be solved in each period. Many simulations are required to remove the simulation error because market demographics, qualities and format choices can evolve in many different ways. On average, I found that it required an average of just over 7,000 simulation paths for the estimate of expected future revenues to converge to within 1% of its true value (estimated using 11,000 simulations). Instead I use 220 forward simulations per observation and use an estimator which allows for simulation error.

As is standard in the dynamic games literature, I assume that I observe the same state space as the firms. As a result there is no v_2 when the value function V_s is defined prior to the private information ε^Fs being realized. This case corresponds to Pakes et al.'s Example 1 and several of their empirical examples. Substituting (23) into (22) and using $E(\nu_{1,s,\varsigma_s}|\mathcal{I}_s) = 0$

$$E[r(\varsigma_s^*, \varsigma_{-s}^*, x^0; \theta) - r(\varsigma_s', \varsigma_{-s}^*, x^0; \theta)|z_s] \geq 0 \tag{24}$$

where $z_s \in \mathcal{I}_s$.

(24) can be turned into an estimating moment inequality by specifying a set of non-negative instrument functions $h(z_s)$, interacting them with the inequalities and taking sample averages across observations

$$\frac{1}{S}\sum_{s=1}^{S}\left[\left(r(\varsigma_s^*, \varsigma_{-s}^*, x^0; \theta) - r(\varsigma_s', \varsigma_{-s}^*, x^0; \theta)\right) \otimes h(z_s)\right] \geq 0 \tag{25}$$

The ν_1 errors are "averaged out" across observations. The number of moment inequalities can be increased by expanding the set of instruments $h(z_s)$ or increasing the number of alternative strategies considered. The parameters are estimated by finding the θs which satisfy the inequalities (or minimize violations if there are no parameters for which all the inequalities hold). Estimation is particularly simple when r is a linear function of θ. Pakes et al. prove consistency of the estimator (as the number of observations increases) and show how to construct two types of confidence interval.[25]

Applying Pakes et al. (2006) to Estimate Repositioning Costs. In my setting, the $r(.)$s are the simulated value functions and the ν_1s are additively separable simulation errors in measuring station revenues (I will come back to simulation error in the other components of expected payoffs in a moment). There are three parameters to estimate, θ_1, θ_2 and σ. I perform the estimation separately for six groups of markets of different sizes, so that the parameters can vary freely between the groups.

[25] It is not known how to analytically correct these confidence intervals for estimation error in the first step. The most obvious solution would be to bootstrap the confidence intervals by repeating the forward simulations for different draws from the first step parameters. This would be very time consuming and I have not done it. However, I do examine how the second stage estimates change when I change the specification for the transition of unobserved station quality which directly affects how attractive switching is. The second stage parameter estimates change relatively little in this case.

I use the simplest possible application of the Pakes et al. methodology to my setting. I define the $h(z_s)$s to be a set of constants and consider four alternative policies which provide lower and upper bounds on θ_1, and upper bounds on θ_2 and σ. I add the natural restrictions that $\theta_2 \geq 0$ (fixed costs are positive) and $\sigma \geq 0$ (the scale parameter on the ε^Fs are non-negative). As a result, the system of inequalities for each group of markets g reduces to

$$\frac{1}{S_g}\sum_{s\in g}\left[\begin{array}{c}(\widehat{\mathbf{R}_{s,\varsigma_s^*,\varsigma_{-s}^*}} - \widehat{\mathbf{R}_{s,\varsigma_s',\varsigma_{-s}^*}}) - \theta_1(\widehat{\mathbf{S}_{s,\varsigma_s^*,\varsigma_{-s}^*}} - \widehat{\mathbf{S}_{s,\varsigma_s',\varsigma_{-s}^*}}) \\ -\theta_2(\widehat{\mathbf{F}_{s,\varsigma_s^*,\varsigma_{-s}^*}} - \widehat{\mathbf{F}_{s,\varsigma_s',\varsigma_{-s}^*}}) + \sigma(\widehat{\boldsymbol{\varepsilon}^F_{s,\varsigma_s^*,\varsigma_{-s}^*}} - \widehat{\boldsymbol{\varepsilon}^F_{s,\varsigma_s',\varsigma_{-s}^*}})\end{array}\right] \geq 0 \text{ for 4 alternative } \varsigma_s' \tag{26}$$

$$\theta_2 \geq 0, \sigma \geq 0$$

A nice feature of these inequalities is that additively separable simulation error in the $\mathbf{S}$, $\mathbf{F}$, and $\boldsymbol{\varepsilon}^F$ terms should also be averaged out across observations.

I now describe the alternative strategies. A strategy specifies a set of cutoffs for the ε^Fs, as functions of the observed state variables, which lead to different format choices. A strategy implies a probability for each format choice in each state prior to the realization of the ε^Fs. My alternative strategies vary the choice probabilities and, equivalently, imply different cutoffs for the ε^Fs.

The logic behind each of the alternative policies can be seen writing the inequality as

$$(\mathbf{R}^* - \mathbf{R}') - \theta_1(\mathbf{S}^* - \mathbf{S}') - \theta_2(\mathbf{F}^* - \mathbf{F}') + \sigma(\boldsymbol{\varepsilon}^{F*} - \boldsymbol{\varepsilon}^{F\prime}) \geq 0 \tag{27}$$

and rearranging it to provide bounds on the parameters of interest

$$\theta_1 \geq \frac{(\mathbf{R}' - \mathbf{R}^*)}{(\mathbf{S}' - \mathbf{S}^*)} - \theta_2\frac{(\mathbf{F}' - \mathbf{F}^*)}{(\mathbf{S}' - \mathbf{S}^*)} + \sigma\frac{(\boldsymbol{\varepsilon}^{F\prime} - \boldsymbol{\varepsilon}^{F*})}{(\mathbf{S}' - \mathbf{S}^*)} \text{ if } (\mathbf{S}' - \mathbf{S}^*) > 0 \tag{28}$$

$$\theta_1 \leq \frac{(\mathbf{R}' - \mathbf{R}^*)}{(\mathbf{S}' - \mathbf{S}^*)} - \theta_2\frac{(\mathbf{F}' - \mathbf{F}^*)}{(\mathbf{S}' - \mathbf{S}^*)} + \sigma\frac{(\boldsymbol{\varepsilon}^{F\prime} - \boldsymbol{\varepsilon}^{F*})}{(\mathbf{S}' - \mathbf{S}^*)} \text{ if } (\mathbf{S}' - \mathbf{S}^*) < 0 \tag{29}$$

$$\sigma \leq \frac{(\mathbf{R}^* - \mathbf{R}')}{(\boldsymbol{\varepsilon}^{F\prime} - \boldsymbol{\varepsilon}^{F*})} + \theta_2\frac{(\mathbf{F}' - \mathbf{F}^*)}{(\boldsymbol{\varepsilon}^{F\prime} - \boldsymbol{\varepsilon}^{F*})} + \theta_1\frac{(\mathbf{S}' - \mathbf{S}^*)}{(\boldsymbol{\varepsilon}^{F\prime} - \boldsymbol{\varepsilon}^{F*})} \text{ if } (\boldsymbol{\varepsilon}^{F\prime} - \boldsymbol{\varepsilon}^{F*}) > 0 \tag{30}$$

$$\theta_2 \leq \frac{(\mathbf{R}' - \mathbf{R}^*)}{(\mathbf{F}' - \mathbf{F}^*)} - \theta_2\frac{(\mathbf{S}' - \mathbf{S}^*)}{(\mathbf{F}' - \mathbf{F}^*)} + \sigma\frac{(\boldsymbol{\varepsilon}^{F\prime} - \boldsymbol{\varepsilon}^{F*})}{(\mathbf{F}' - \mathbf{F}^*)} \text{ if } (\mathbf{F}' - \mathbf{F}^*) < 0 \tag{31}$$

Consider an alternative strategy which raises expected revenues (**R**) at the cost of increasing the number of switches (**S**). The fact that this strategy is not chosen implies a lower bound on the sunk repositioning costs as a function of θ_2 and σ (inequality 28). On the other hand, the fact that a strategy which reduces switching but also reduces future revenues is not chosen provides an upper bound on sunk costs (inequality 29). I operationalize the first alternative by changing the station's strategy so that the probability that it remains in its current format falls by 0.05 in every state with the probabilities of every alternative format scaled up proportionally. The second alternative has the station never switching formats. The results are similar varying the size of the changes in strategy unless the changes are very small (as I discuss below).

Pakes et al. provide a graphical interpretation of their procedure (p. 55). Figure 4(a) shows the bounds constructed using these alternative strategies in (θ_1, σ) space where the inequalities are averaged over stations in markets with between 3 and 5 million people and $\theta_2 = 0$. A format switch tends to yield a higher value of ε^F, so that as σ increases higher sunk costs are required to rationalize why stations rarely switch formats. This causes the bounds to slope upwards.

An upper bound on σ can be found using an alternative policy which increases $\boldsymbol{\varepsilon}^F$ while reducing future revenues, holding switching roughly constant (inequality 30). I construct an appropriate alternative strategy using a feature of the multinomial logit choice model. For a given set of alternatives, the expected value of the ε^F associated with the chosen alternative increases as the choice probabilities are made more equal.[26] The specific alternative strategy which I consider leads to the station not changing the probability that it remains in its current format but equalizing the probabilities of choosing each alternative format.[27] Figure 4(b) adds this bound to the diagram. The resulting upper bounds on (θ_1, σ) are (\$47m, \$4.7m) and the lower bounds are (\$6.4m, \$0m). Figure 5 shows that the diagrams constructed for other market groups are qualitatively very similar, although the scale of

[26]This results from the εs being iid across choices. An agent who chooses the alternative with the highest ε (disregarding other features of the choice) will choose each alternative with equal probability.

[27]A specific example may help to provide more intuition. AM stations rarely choose Rock and frequently choose News/Talk. This presumably reflects the fact that AM stations expect higher revenues in News than in Rock. On the other hand, if AM stations simply maximized the ε^Fs associated with their format choices there would choose Rock with the same probability as News. I can estimate how much lower expected revenues and higher expected ε^Fs would be if an AM station was to choose News and Rock with equal probability and this lets me construct an upper bound on σ.

the axes varies with market size.

An upper bound on per-period fixed costs can be found by considering an alternative strategy which reduces the number of periods the station is on-air (**F**) while also reducing revenues (inequality 31). The alternative strategy increases the probability than an active station goes off-air by 0.05, with the other choice probabilities reduced proportionally.[28]

5.6.3 Alternative Second Step Estimators

I use the moment inequality approach because it allows me to consistently estimate the parameters even when there is some error in the simulated payoffs of each station. Estimators such as Maximum Likelihood (using observed station choices) or moment estimators which calculate choice probabilities will not produce consistent estimates because they use non-linear transformations of the simulated payoffs.

A disadvantage of the moment inequality approach is that it produces only bounds on the parameters. However, one can approximate moment equalities (representing the first-order conditions of the firm's maximization problem) using small perturbations of station strategies. I have experimented with this approach and when the perturbations are not too small it produces estimates of repositioning costs which are similar to the (reasonable) upper bound estimates produced using the inequalities. When very small perturbations are used, the results become sensitive to the number of forward simulations. This suggests that the larger changes in strategy considered when calculating the moment inequalities may also be helpful in dealing with simulation errors.

6 Results

This section presents the empirical results. I estimate the model using data from Spring 1997 to Spring 2006 for 100 markets (listed in Table 5) where less than 6% of radio listening is to out of

[28] A lower bound on per-period fixed costs can be estimated by increasing the probability that off-air stations become active. However, many of my off-air stations have lost their licenses or are waiting to be licensed so they may prevented from entering even if it was profitable to do so.

market stations.[29] I limit the sample in this way to avoid modelling interactions between markets. In the second step I simulate the model for each station observed in the data in Fall 2004.

I also make two additional adjustments to the data. First, radio listening has declined since the mid-1980s and real revenues per listener have increased. Since 2001 these trends have roughly offset each other. To avoid modelling these trends I remove the national trend from the share data and, when simulating the model forward, I assume that real revenues per listener will remain fixed at their 2004 levels.

Second, BIAfn does not report the market shares of stations which fail to meet Arbitron's Minimum Reporting Standards (Arbitron (2002)). These stations have low market shares (generally less than 0.3% of radio listening each), but they can account for as many as 25% of all stations. To avoid imputing shares for such a large proportion of the sample, I drop stations which are missing data for over half of the sample periods (17% of stations) and impute a share for the remainder based on how many quarters are missing and the share of the smallest reported station in the market-quarter.

6.1 First Step: Listener Demand

Table 6 presents the estimated coefficients from the demand model and the processes governing station quality.[30] Specification A is the model described above. The demographic format taste parameters show the expected pattern, with, for example, females preferring Adult Contemporary and disliking Rock, and most of these coefficients are precisely estimated. The standard deviations of the random components of format tastes are small and insignificantly different from zero. This finding is consistent with demographics capturing most of the systematic differences in individuals' tastes for different types of programming within markets.[31] The standard deviation of the random coefficient

[29] A little over 12% of stations in this subsample of markets have listeners in other markets. I assume that stations do not consider revenues they get from listeners in other markets. This is plausible because local advertisers will place less value on reaching listeners in other markets (the BIAfn revenue data suggests that an out of market listener counts for about 20% of the value of a home market listener).

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

[31] The market-format fixed effects should capture systematic differences in format preferences across markets.

on the commercial radio constant is also quite small, indicating that there is a reasonable degree of substitution with the outside good which includes non-commercial stations and the fringe stations which are too small to be included in the sample.

The coefficients on the fixed station quality characteristics are sensible, with greater signal coverage and more powerful transmitters associated with higher station quality. The small number of out of market stations are estimated to be of lower quality, and the coefficient on the dummy included for stations with imputed shares is also negative as these stations, by definition, have small shares. AM band stations are, as expected, estimated to have higher quality in the News format than formats such as Rock and Urban. However, AM stations are estimated to have higher quality in Adult Contemporary and CHR than in News, even though there are very few AM AC or CHR stations.

The final part of the table reports the coefficients for the processes controlling unobserved station quality. The ρ^{ξ} parameters are less than one so that the processes are stationary. While quality is more persistent for stations staying in the same format, it is also persistent ($\rho_2^{\xi} = 0.7$) for stations which switch formats. The μ_2^{ξ} coefficient indicates the quality falls on average in the period following a switch even though listenership increases. However, this quality decline is not statistically significant: quality is largely transferred across formats.

Figure 1 shows that listenership increases for two periods following a switch, rather than adjusting to a new level immediately. Specification B captures this effect by adding an additional constant to the quality evolution process (4) for stations which changed formats one period earlier. The coefficient is positive and statistically significant, with the other transition parameters remaining almost the same as in specification A (this also applies to the other coefficients which I do not report). The most obvious interpretation of this increase in quality is that listenership increases as listeners become aware of the station's new format with some additional benefit arising because of novelty or from investments undertaken at the time of switching which have not been modelled. Allowing for this quality increase tends to makes switching more attractive and, a result, increases how large sunk repositioning costs have to be to explain why stations rarely switch. In what follows I use the specification B results, but show how the second step parameters change if I use specification A instead.

Figures 6(a) and (b) show the pdfs of the innovations in unobserved station quality (the residuals from the quasi-differenced moments) and Figure 6(c) shows the pdf of quality itself (ξ_{smt}). All of the distributions are close to bell-shaped with more weight in the tails than one would expect given normal distributions. Most of the weight in the tails of the innovation distributions comes from small stations for whom shares and changes in share may be affected by my imputation or Arbitron's mismeasurement. In the analysis which follows I draw the innovations in quality from the empirical distributions of innovations for stations with shares above the 25^{th} percentile, although the fit of the model is very similar using a wide range of cutoffs.[32]

I can also compute how well the demand model and innovation processes perform at predicting how listenership changes over time. To do this, I use the estimates of station quality in period t, simulate (one set of) changes in station quality and calculate stations' market shares in their $t+1$ formats with $t+1$ market demographics. Figure 7 and Table 7 compare the changes in share seen in the data with those simulated from the model. The actual and simulated distributions match closely for both switchers and non-switchers.

One can also calculate the model's performance at predicting changes for individual stations. This can be done either by using just one simulation or using multiple simulations (I use 20). The correlation between these average predicted changes and the changes seen in the actual data for format switchers is 0.56.[33] The correlation for stations remaining in the same format is lower, 0.14. This is not surprising as non-switchers are less affected by the type of structural change in product positioning which the estimated demand model is designed to capture.

[32] If no cut-off is used the changes in share for larger stations have greater variance than those observed in the data. The fit of the model is also similar when separate innovation processes are estimated for small and large stations. The demand system parameters are also essentially identical in this case.

[33] As a benchmark one can compare this correlation with the correlation between a single simulation and the mean from 20 different simulations. This correlation is 0.62, indicating that the model only does a slightly worse job of predicting what happens than would be expected if the model was perfectly specified.

6.2 First Step: Revenue Function

Table 8 reports the coefficients from several specifications of the revenue function. The revenue function is estimated using BIAfn's revenue data and estimates of audience composition from the demand model. The first specification assumes a price per listener which does not vary with the size of a station's listenership but does vary with listener demographics. Females are estimated to be more valuable than males, listeners aged 25-49 to be more valuable than older or younger listeners and whites to be more valuable than blacks or Hispanics. These demographic coefficients are similar across the specifications. The bottom section of the table provides some statistics on the performance of the revenue model in predicting changes in annual revenues given the changes in listenership. The simplest specification underestimates the average increase in (nominal) revenues for non-switchers and overestimates them for switchers, although the correlations between predicted and observed changes in revenues are reasonable in both cases.

The second specification allows for effects of format competition, common ownership as well as an additional effect on revenues in the year following a change in format (when a station may carry fewer commercials or discount commercial time while it develops relationships with new advertisers). Common ownership with an additional station in the format increases revenues per listener by 2%.[34] Competition reduces revenues by a small and barely significant amount (0.2%). The absence of a competition effect is consistent with advertising prices being set in a broader advertising market. The specification also reveals a large, direct effect of format switching on station revenues as prices per listener are estimated to fall by 14% in the year following the format switch.

The last two specifications allow for prices per listener to vary with the number of listeners. This is partly motivated by Fisher et al.'s (1980) finding that advertising prices charged by local TV stations increase with audience size. The third specification allows for prices to vary with the difference between the station's market share and the market average. Consistent with Fisher et al., prices per

[34] This could be rationalized by (i) common owners being able to offer advertisers bundles of ads on different stations which allows them to extract more advertiser surplus or (ii) by being able to exercise some market power over either listeners (making them listen to more commercials) or advertisers. In either case the common ownership effect is relatively small.

listener increase with station size and allowing this effect increases the predicted change in revenues for format switchers, as they tend to gain listeners. The predicted change in revenues for switchers and non-switchers is lower than the observed changes by similar amounts.

The final specification allows the prices per listener in each of the 18 demographic groups to vary with the proportion of the station's listenership who are in that group. This is motivated by the idea that advertisers may value more homogenous audiences. However, the coefficient is negative and significant. There is no obvious explanation for a negative effect and in using the revenue function below I use the results from the third specification.

6.3 First Step: Station Policy Functions

Table 9 reports the coefficients from the multinomial logit estimates of station strategies. An advantage of the parametric specification is that it is easy to see whether the signs of the coefficients are sensible.

The first part of the table shows the coefficients on variables that one should think of as affecting the intrinsic attractiveness of a format. The pattern of coefficients is sensible. For example, large and growing Hispanic populations make stations more likely to choose the Spanish format. Larger black populations make stations more likely to choose Urban and Religious formats, although black growth is not estimated to have significant effects. This is probably because black growth rates show less variation than Hispanic growth rates during my sample period. The coefficients on the measures of market-format attractiveness (the market-format fixed effects from the demand system) are positive, as one would expect, but they are generally insignificant.[35]

The second part reports the coefficients on variables reflecting competition from other stations. As expected, most of the coefficients are negative (more competition makes it less attractive for a station to choose the format). A station is also more likely to stay in a format if it is the largest station and, in general, stations with larger shares are less likely to switch. The third part lists the

[35] I have to impute qualities for market-formats in which stations are never observed. Religious formats in markets outside of the South and Spanish formats in markets with few Hispanics make up the majority of the cases. I assume that market-format attractiveness in these markets is equal to the 25% percentile of markets where attractiveness can be estimated. The results do not appear to be sensitive to the percentile used.

coefficients on interactions between format and band. I allow the coefficients to differ depending on whether stations are already in the format (Stay x) or are in a different format (Switch x). The AM x Switch coefficients are consistent with the pattern in Table 2 that AM stations are more likely to switch to talk programming (News and Religious). The market size interactions indicate that there is less switching, conditional on the other variables, in larger markets.

The final part reports the coefficients on the ownership variables included as controls, as well as a miscellaneous selection of other variables. The national ownership variables indicate that stations are more likely to switch stations into formats where they own other stations (in any market). The magnitude of the effect is largest for Spanish, suggesting that there may be larger economies of scope from operating stations in the same language. There is also a highly significant effect that stations which have undergone recent ownership changes are more likely to switch formats, suggesting that the optimal format choice may differ from owner-to-owner. However, the within market ownership effects are much weaker: a station is slightly (but not significantly) more likely to leave a format where it has sister stations, but it is also more likely to switch to a format where it has sister stations. There are no significant effects of other firms owning multiple stations in a format. Stations which have switched formats in the previous year (Recent Switch x) are slightly, but not significantly, more likely to make a further switch.

One can also calculate a pseudo-R^2 statistic by comparing the maximized log-likelihood with the log-likelihood when the model only contains a constant for staying in the same format. The additional variables explain just over 14% of the variation in station switching decisions. This compares favorably with the pseudo-R^2s reported in Ryan (2005) and Beresteanu and Ellickson (2006).

6.4 First Step: Demographic Transitions

I estimate the demographic transition process using data from all markets, not just the 100 markets used to estimate the rest of the model. The estimates are

$$g_{emt} = \underset{(0.057)}{0.863} g_{emt-1} + \underset{(0.000)}{0.002} + \nu^{D}_{emt} \tag{32}$$

and the standard deviation of ν^{D}_{emt} is 0.0100. This implies that average long-run population growth of 1.5% per year.

6.5 Second Step Estimates: Sunk Repositioning Costs

With the first step estimates in hand, I use the moment inequality estimator described above to bound sunk repositioning costs. Table 10(a) show the bounds and associated confidence intervals for six different groups of markets which differ in size. The estimates assume that the parameters are the same for each station within each market group. In LA and Chicago, the lower and upper bound estimates of θ_1 are \$700,000 (4% of annual revenues for the average station) and \$81 million (over 4 times annual revenues).

The upper bound estimates of mean sunk repositioning costs may seem implausibly large, but if the ε^Fs represent heterogeneity in repositioning costs then the mean will not reflect repositioning costs paid by stations which choose to switch formats. The table also reports the estimated average repositioning costs of stations switching formats during the sample period. This is calculated as the expected value of $\theta_1 - \sigma(\varepsilon^F_a - \varepsilon^F_b)$ where ε^F_a is the ε^F associated with the chosen format and ε^F_b is the ε^F associated with remaining in the station's current format.[36] As the estimate of σ is zero at the lower bound estimate of θ_1, the estimated lower bound of repositioning costs paid is just $\underline{\theta_1}$. On the other hand, the upper bound average sunk repositioning cost of switchers is much lower than $\overline{\theta_1}$. In LA and Chicago the upper bound estimate is \$11.5 million or 64% of annual revenues for the average

[36] This expected value is estimated by simulation using the conditional choice probabilities estimated in the first stage.

station. Total sunk repositioning costs paid, at the upper bound estimates, by format switchers in LA and Chicago during the sample period are estimated to be \$727 million. During the same time period total revenues in these markets were around \$16.3 billion. The average cost of reduced revenues following the format switch was \$1.9 million (\$120 million total).

These estimates of repositioning costs can be compared with the "back of the envelope" estimates of the present discounted value of revenue gains accruing to switchers reported for 5 markets in Table 3. For Chicago, the estimated revenue gains per switcher was \$29 million which is greater than the upper bound estimate of sunk repositioning costs paid by switchers. This is not surprising as there are several reasons for believing that the back of the envelope assumptions should lead to estimates which are too high. For example, the marginal switcher should expect to gain fewer listeners than the average switcher used in Table 3; a switcher may not expect to maintain its increase in share forever; and, many of the observed switchers move to formats such as Spanish where listeners are less valuable to advertisers.

The upper bound estimates fall as market size decreases. This pattern is expected, as there is at least as much switching in smaller markets as larger ones, even though station revenues are smaller.[37] It also consistent with marketing costs being a large component of sunk repositioning costs as the costs of advertising per listener share point will be higher in markets with larger populations. In addition, a station may also have to market itself to a greater number of potential advertisers. On the other hand, the costs of replacing staff or programming libraries or of hiring format consultants would seem likely to be similar across markets, suggesting that these costs are less important.

I assume that fixed costs are only paid by stations in periods when they are on-air. The upper bound estimate of these costs is identified from the fact that if they are too high then stations would prefer to switch to Dark which we rarely see.[38] In most of the market groups the upper bound

[37] The lower bound estimates suggest that sunk switching costs are small in all markets (the second market group is an exception) which would also explain why we can observe switching in smaller markets.

[38] I assume that a station's unobserved quality evolves in the same way when it is Dark as it does in active formats, except that I assume that it does not experience the jump in quality in the second period following a switch. This assumption also tends to make it less attractive for a station to switch to Dark.

estimate is around 66% of the revenues of the average station, being a slightly higher percentage in smaller markets. These estimates are consistent with measures of revenues and operating income reported by publicly-traded radio companies.[39]

The modelling assumption that a radio station's costs do not vary with its listenership is not quite right. Licensing fees for music and syndicated programming increase with station revenues.[40] Although it is difficult to identify stations' marginal costs using only information on format choices and revenues, the way in which the estimates of sunk repositioning costs would change if stations were only to keep a proportion of any increase in revenues as profit is clear from inequalities (28)-(30). For example, if 90% of any revenue increase is kept then the constants on the right-hand side of inequalities would be multiplied by 0.9, reducing the estimated values of θ_1 and σ.

Table 10(b) shows how the estimated parameters change when quality transition specification A is used, so that there is no systematic increase in unobserved station quality following a format switch. As a result switching becomes less attractive and lower repositioning costs rationalize how rare switching is. However, the change in the bounds of θ_1 is relatively small. For example, in markets with between 500,000 and 1 million people, the lower bound estimate of θ_1 falls from \$100,000 to -\$500,000 and the upper bound estimate falls from \$10.3 million to \$9.1 million.

6.6 Applications of the Model

While the richness of the estimated model prevents me from resolving it to conduct certain counterfactuals (e.g., the effects of a repositioning subsidy), it is possible to use the first stage estimates to learn about some of the effects of format switching and how sensitive format choices are to changes in the environment (state space). I consider two examples here: first, how switching observed during the sample period affected listeners and revenues, and second, how sensitive positioning is to changes

[39] For example, Clear Channel reported that operating income was 38% of revenues for its radio stations in its 2004 10-K filing. Cumulus, a radio company operating in medium-sized and smaller markets, reported that operating income was 25% of revenues.

[40] The performing rights agencies ASCAP, BMI and SESAC charge broadcast radio stations a proportion of their revenues. For example, ASCAP charged stations with annual revenues above \$150,000 a rate of 1.65% of revenues for a blanket license in the late 1990s (http://www.ascap.com/licensing/radio/radiofaq.html). Syndicated programming is typically sold by allowing the syndicator to sell a certain number of minutes of advertising time on a station.

in market demographics (relatively permanent demand shocks).

6.6.1 Effects of Format Switching 1997-2006

I use the demand and quality transition estimates to estimate how listenership and revenues changed due to observed format switching. To be precise, I compare listenership and stations revenues in Spring 2006 given observed format switching with a simulated estimate of what they would have been if stations had remained in their Spring 1997 formats but market demographics had evolved in the same way as they did in the data. I report changes in per period revenues (i.e., flows) rather than discounted future values.

The upper part of Table 11 shows the difference in listenership between these two scenarios for seven demographic groups. In larger markets, observed format switching led to quite large increases in the listenership of Hispanic and blacks, small increases for women and small decreases for whites and people over 50. The increase in listenership of Hispanics is consistent with the 72% increase in the number of Spanish language stations in the first three groups of markets. The increase in black listenership may seem more surprising but it is explained by the 28% and 17% increases in the number of Urban and Contemporary Hit Radio stations which are popular with blacks. The decline in older listenership is explained by the decrease in the number of Other Music (e.g., Easy Listening, Variety, Middle of the Road and Jazz) stations which attract mainly older listeners.

Format switching caused broader increases in listenership in smaller markets. This is because there was more switching out of Dark (entry) in these markets and these switches unambiguously increase the listenership of every demographic group.[41]

The lower part of Table 11 shows how format switching effects the revenues of switching and non-switching stations. Berry and Waldfogel (1999) argue that when an additional station enters a radio market listeners are taken from existing stations. This externality can lead to "excess entry". On the other hand, when a station switches between active formats it frequently only changes which group of

[41] In the first two market groups there are 1 and 5 examples of stations moving from Dark, whereas there 33, 25, 25 and 47 cases respectively in the smaller market groups.

stations it takes listeners from. In larger markets, there is little switching from Dark (entry) so that the increase in revenues for switchers is not associated with a significant net change in the revenues of non-switchers. Figure 8 shows the distribution of changes in revenue for non-switchers in the second group of markets, with stations facing more competition as a result of format switching tending to lose revenues. In smaller markets there is more switching from Dark. The entering stations obviously gain revenues, but their entry reduces the revenues of both non-switchers and stations switching between active formats.

6.6.2 Sensitivity to Demand Shocks

I use observed station strategies to examine how sensitive format choices are to shocks in demand. Table 4 (long differenced IV) shows that format availability does respond to the relatively slow changes in market demographics seen in the data.[42] Here, I illustrate the response implied by the estimated policy function to a larger change in demand using the Minneapolis-St. Paul market as an example. In Fall 2004 there were no Urban stations in this market and only a small (5.5%) black population. I shock the market by making 20% of the white population black, and then simulate the model to see how quickly we should expect stations to enter the Urban format.[43] Based on the demographics of the shocked market, a between market regression predicts that there should be 3.4 Urban stations.

Figure 9 shows what happens to the number of Urban stations when I simulate the model for twenty years 100 times. On average, there is one Urban station within 2 years, two Urban stations within 4 years and three after 8 years. After this point, the number remains stable at between 3 and 4 stations. Thus, despite the presence of significant repositioning costs, the results suggest that format availability adjusts quite rapidly to demand shocks. This relatively rapid adjustment is interesting because many policy analyses (e.g., of mergers) considers whether repositioning could take place in a

[42] Waldfogel (2003) also shows that there are more black (Hispanic)-orientated stations in markets with more blacks (Hispanics) using cross-sectional data.

[43] I assume that the growth rates of the black and white populations evolve from their pre-existing (i.e., non-shocked) levels, so that there is not a massive spike in black growth. Of course, a limitation of this exercise is that the policy function can only approximate station policies at points seen in the data. Once we step to points in the state space well outside the range in the data, the approximations may be less reliable.

period of one to two years.

7 Conclusion

The last 15 years have seen considerable progress in modelling both static and dynamic consumer demand for differentiated products. However, there has been relatively little work modelling the supply of differentiated products, and this is a potential problem for understanding the effects of any kind of shock which might lead to firms wanting to change the products that they offer.

I estimate a dynamic model of commercial radio markets which provides insights into what drives product repositioning as well as estimates of how expensive repositioning is for firms and how it affects listeners. I find significant evidence of two types of repositioning cost. First, stations tend to receive lower revenues per listener following a format switch. This reduction is consistent with it taking time for stations to develop relationships with a new set of advertisers. Second, there are sunk costs associated with switching. There are many potential sources of these costs, such as marketing, hiring format consultants, replacing staff or updating the station's programming library, but the fact that they are larger in larger markets suggests that marketing costs may be the most important. For stations which choose to switch formats these costs could be as large as one year's revenues, but these costs are not large enough to prevent markets adjusting quite quickly to changes in demand.

The quantitative results are specific to the commercial radio industry which is one of the industries where the antitrust authorities have considered whether repositioning could constrain market power following mergers. More generally, the paper provides a framework for examining repositioning in any industry with evolving product variety. The framework can handle many firms and numerous types of product which appeal to different kinds of consumer.

Understanding the potential role of repositioning following mergers was one of the primary motivations for this paper. My results suggest that radio stations may only switch formats if they expect to realize quite significant gains. However, it is important to acknowledge that multi-product ownership is currently modelled in a limited way. In particular, I control for the effects of multi-product ownership on stations' policies but I do not explicitly model the dynamics of product selection by multi-product firms and I do not model how firms expect product ownership to change in the future. Modelling multiproduct firms in a more sophisticated way and estimating how mergers affect product selection through market power, business cannibalization and economies of scope, both within and across markets, are important topics for future research.

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A Details of the Forward Simulation Procedure

In this Appendix I describe the forward simulation procedure which I use to calculate the components of stations' expected future payoffs.

A.1 Simulations Using Actual Station Strategies

The simulation procedure goes through the following steps in each time period.

1. the random coefficients demand model is solved, given station formats, qualities and market demographics, to give the listenership of each station in each of the 18 demographic groups. I use 10 Halton draws per demographic group for the v_i^Fs;

2. the estimated revenue function is used to calculate discounted revenues for the station of interest. These are added to the sum of discounted revenues from previous periods. The calculation is done assuming that the station is independently owned. If the station is not Dark a discounted indicator is added to the count of how many periods the station has been on-air. This count is used in calculating expenditure on fixed costs;

3. the variables which affect the multinomial logit format choice problem for each station are calculated. These include measures of competition and demographics which may have changed since the previous period. All stations are assumed to be independently owned;

4. the multinomial logit choice probabilities for each station are calculated and compared with random draws from a uniform distribution to simulate a choice for each station;

5. if the station of interest switches to an active format, a discounted indicator is added to the count of how many times it has switched formats. The choice probabilities are used to calculate the expected discounted value of the ε^Fs associated with its format choice. The multinomial

logit structure of its problem gives this expected value a convenient analytic form

$$E(\varepsilon_f|f \text{ chosen},\mathcal{S},\varsigma_s) = 0.57721 - \log(\Pr{}_{fs}(\mathcal{S},\varsigma_s)) \tag{33}$$

where $\Pr_{fs}$ is the probability that format f is chosen by station s given observed state space $\mathcal{S}$ and strategies ς_s.

6. the evolution of station qualities, conditional on current and previous format choices, is simulated. The random components are drawn from the appropriate empirical distribution of observed quality innovations;

7. the evolution of demographics is simulated, by assuming that the same growth rate applies to each of the demographic groups of the same ethnicity/race. The census data only provides annual changes in growth rates, so I also only simulate changes in annual growth rates every two periods, assuming that the same growth rate applies within two periods each year; and,

8. station formats are updated.

As some stations only switch formats with low probability, one would need many simulations to get even a small number of simulations where the station switches formats. Therefore, I simulate the expected payoffs from making each format choice in the first period 20 times and weight these simulations using the first period choice probabilities. Each simulated path goes forward for 60 periods with a discount factor of 0.95. Results are similar using paths of 80 periods.

A.2 Simulations Using Alternative Station Strategies

The alternative strategies involve changing the conditional choice probabilities of the station of interest. The strategies of other stations remain the same as before. Therefore the only change to the above procedure is that in step 4, I recalculate the choice probabilities for the station of interest according to the alternative policy that I am using.

Table 1: Formats and Demographics

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

Notes: Female and age figures based on station-level Arbitron data for Spring 2006. Black and Hispanic figures based on Arbitron estimates for Spring 2004 reported in 2005 *Radio Today* publication. There are only a small number of Ethnic stations which fall primarily in a few markets, such as Honolulu.

Table 2: Format Switching Patterns

FM Stations

From	**Number of station-qtr observations**	**Proportion switching out**	Dark	AC	CHR	Cntry	Old	Rock	Urban	News	OtherM	Relig	Span
			Of stations switching out, proportion switching to										
Dark	1,956	0.15		0.17	0.06	0.15	0.09	0.22	0.06	0.03	0.09	0.06	0.05
Adult Contemporary	11,508	0.04	0.01		0.25	0.10	0.13	0.24	0.07	0.05	0.09	0.04	0.04
CHR/Top 40	6,243	0.04	0.00	0.29		0.07	0.06	0.21	0.22	0.03	0.03	0.04	0.04
Country	10,455	0.03	0.01	0.19	0.12		0.12	0.23	0.06	0.05	0.08	0.04	0.09
Oldies	5,592	0.06	0.01	0.26	0.09	0.13		0.31	0.09	0.03	0.04	0.01	0.03
Rock	13,466	0.03	0.00	0.29	0.13	0.09	0.14		0.09	0.07	0.07	0.04	0.08
Urban	4,625	0.03		0.15	0.32	0.06	0.10	0.11		0.04	0.06	0.09	0.07
News/Talk/Sports	1,251	0.05	0.03	0.10	0.12	0.13	0.12	0.28	0.03		0.03	0.04	0.10
Other Music	3,164	0.08	0.01	0.26	0.13	0.12	0.06	0.19	0.09	0.04		0.04	0.06
Religion	2,656	0.04	0.04	0.23	0.10	0.06	0.11	0.10	0.15	0.04	0.11		0.06
Spanish	3,005	0.02	0.04	0.12	0.30	0.05	0.05	0.09	0.16	0.04	0.14	0.02	

AM Stations

From	**Number of station-qtr observations**	**Proportion switching out**	Dark	AC	CHR	Cntry	Old	Rock	Urban	News	OtherM	Relig	Span
			Of stations switching out, proportion switching to										
Dark	478	0.17	0.00	0.03	0.00	0.06	0.08	0.04	0.04	0.34	0.24	0.13	0.06
Adult Contemporary	496	0.10	0.04		0.00	0.14	0.08	0.00	0.02	0.27	0.37	0.02	0.06
CHR/Top 40	49	0.24	0.00	0.00		0.00	0.17	0.08	0.08	0.33	0.25	0.00	0.08
Country	1502	0.08	0.03	0.01			0.06	0.03	0.02	0.55	0.21	0.06	0.03
Oldies	905	0.10	0.00	0.04	0.00	0.10		0.03	0.01	0.52	0.19	0.08	0.02
Rock	121	0.28	0.03	0.03	0.06	0.09	0.12		0.09	0.26	0.18	0.09	0.06
Urban	1109	0.05	0.05	0.00	0.00	0.02	0.05	0.02		0.29	0.10	0.36	0.10
News/Talk/Sports	13066	0.02	0.06	0.03	0.01	0.16	0.09	0.03	0.02		0.29	0.14	0.17
Other Music	4240	0.06	0.01	0.05	0.01	0.08	0.11	0.03	0.01	0.58		0.05	0.07
Religion	3539	0.02	0.07	0.01	0.03	0.03	0.04	0.00	0.25	0.38	0.11		0.09
Spanish	2578	0.02	0.02	0.03	0.00	0.03	0.05	0.02	0.02	0.55	0.17	0.12	

Table 3: Back of the Envelope Calculation of Revenue Increases Due to Format Switching

Market Name	Population Aged 12 and above 2004 (millions)	Average Price Per Listener 2004 ($)	Implied PDV of Permanent 0.08 Percentage Point Increase in Listenership ($ millions)
Chicago	7.62	472	28.8
Minneapolis-St. Paul	2.58	599	12.4
Memphis	1.03	386	3.2
Anchorage, AK	0.22	625	1.1
Casper, WY	0.06	493	0.2

Notes: See Section 3 for assumptions underlying these calculations

Table 4: Long Differenced Regressions For The Proportion of Home Market Stations in A Market-Format

	AC	CHR	Cntry	Oldies	Rock	Urban	News	Other M	Relig	Spanish	Pooled
Proportion Black	-0.248	-0.201	-0.176	0.233	0.017	0.754**	-0.679	0.198	1.336**	-0.436	-
	(0.651)	(0.430)	(0.629)	(0.575)	(0.590)	(0.370)	(0.716)	(0.721)	(0.553)	(0.352)	
Proportion Hispanic	0.221	-0.225	-0.301	0.481	-0.414	0.127	0.096	0.078	-0.577***	0.604***	-
	(0.273)	(0.180)	(0.268)	(0.240)**	(0.250)	(0.154)	(0.314)	(0.320)	(0.209)	(0.155)	
Out of Market Share	-0.136	0.128	-2.161	-0.839**	-0.225	-0.525**	1.875**	1.999	-8.241***	0.451	-0.189***
(Competition)	(0.705)	(0.237)	(2.124)	(0.390)	(0.319)	(0.226)	(0.798)	(1.047)	(3.011)	(0.420)	(0.059)
Number of market-format quarters	548	548	548	548	548	548	548	548	548	548	5,480

Notes: Standard errors in parentheses. **,*** denote statistical significance at the 5%,1% levels respectively. Regressions use data from the first and last quarters in which the market is observed in the Arbitron ratings data and include quarter and market-format fixed effects. The pooled regression include format x quarter and format x demographic interactions.

I instrument for the Out of Market Share variable in the following way: I calculate the average (across quarters) share of listening in each market to stations which are home to every other market. I then find each station's average (across quarters) share of listening in its home market. I multiply these two numbers together to calculate the predicted share of each out of market station. I then add the predicted shares of all of the out of market stations in a format to create the instrument. This instrument implicitly assumes that an out of market station's choice of format does not depend on the number of home market stations in a format. This is a reasonable assumption for most markets in the data, as out of market stations with significant listenership are typically based in much larger markets and their format choices are unlikely to be affected by the decisions of stations in smaller markets. For example, several Boston stations have significant share of listenership in Worcester, MA, but only a small proportion of their listeners come from Worcester. Worcester stations have few listeners in Boston, so the format choices of Boston stations are unlikely to be influenced by those of Worcester stations.

Table 5 : Markets Used in Estimating the Structural Model

Market Name	Population 000s	Market Name	Population 000s
Los Angeles	10,397	Columbia, SC	445
Chicago, IL	7,399	Des Moines, IA	443
Dallas - Ft. Worth	4,198	Wichita, KS	443
Boston	3,846	Charleston, SC	446
Houston-Galveston	3,788	Spokane, WA	430
Detroit	3,818	Madison, WI	430
Atlanta, GA	3,348	Ft. Wayne, IN	409
Miami-Ft. Lauderdale-Hollywood	3,285	Lexington-Fayette, KY	403
Seattle-Tacoma	3,000	Chattanooga, TN	401
Phoenix, AZ	2,430	Roanoke-Lynchburg, VA	388
Minneapolis - St. Paul	2,459	Augusta, GA	391
St. Louis	2,154	Boise, ID	345
Tampa-St. Petersburg-Clearwater	2,006	Jackson, MS	357
Denver - Boulder	2,026	Reno, NV	329
Pittsburgh, PA	2,037	Shreveport, LA	319
Portland, OR	1,800	Corpus Christi, TX	299
Cleveland	1,797	Quad Cities, IA-IL	298
Sacramento, CA	1,562	Springfield, MO	270
Kansas City	1,450	Eugene - Springfield, OR	274
San Antonio, TX	1,377	Fayetteville, AR	251
Milwaukee - Racine	1,402	Salisbury-Ocean City, MD	267
Salt Lake City - Ogden	1,337	Macon, GA	256
Columbus, OH	1,315	Portland, ME	226
Charlotte-Gastonia-Rock Hill	1,224	South Bend, IN	219
Norfolk-Virginia Beach-Newport News	1,258	Binghamton, NY	217
Orlando	1,187	Anchorage, AK	216
Indianapolis, IN	1,205	Lubbock, TX	204
Las Vegas, NV	1,138	Odessa - Midland, TX	188
Greensboro-Winston Salem-High Point	1,041	Yakima, WA	173
Austin, TX	1,035	Amarillo, TX	178
Nashville	1,011	Traverse City-Petoskey, MI	183
New Orleans	1,061	Medford-Ashland, OR	154
Memphis	1,002	Fargo, ND - Moorhead, MN	144
Buffalo-Niagara Falls, NY	998	Duluth, MN - Superior, WI	173
Jacksonville, FL	936	Abilene, TX	131
Oklahoma City	992	Parkersburg-Marietta, WV-OH	128
Louisville, KY	880	Panama City, FL	121
Richmond, VA	828	Eau Claire, WI	125
Birmingham, AL	823	Monroe, LA	121
Albany-Schenectady-Troy	746	Billings, MT	106
Honolulu	750	Sioux City, IA	102
Tucson, AZ	705	Williamsport, PA	102
Tulsa, OK	693	Grand Junction, CO	97
Grand Rapids, MI	669	Albany, GA	98
Ft. Myers-Naples-Marco Island	590	Harrisonburg, VA	95
Knoxville, TN	580	Rapid City, SD	94
Albuquerque, NM	575	San Angelo, TX	86
Omaha - Council Bluffs	563	Bismarck, ND	78
El Paso, TX	532	Meridian, MS	65
Little Rock, AR	510	Casper, WY	55

Table 6: Listener Demand Model Estimates

	Demographic Effects and Random Coefficients					
	Std Dev of RC	Age 25-49	Age 50 plus	Female	Black	Hispanic
Adult Contemporary	0.1680	0.7755	0.4146	0.5243	-0.5655	-0.6662
	(5.9595)	(0.0292)	(0.1141)	(0.0180)	(0.1619)	(0.2281)
CHR/Top 40	0.0135	-0.8848	-2.5559	0.2818	0.5957	0.0575
	(3.8355)	(0.0093)	(0.0144)	(0.0037)	(0.0663)	(0.0806)
Country	0.0780	0.3722	0.4482	0.0335	-1.9005	-1.6215
	(2.0265)	(0.0185)	(0.0225)	(0.0054)	(0.0578)	(0.0896)
Oldies	0.0004	0.9395	1.3447	-0.1154	-0.8404	-0.6259
	(2.4052)	(0.0264)	(0.0253)	(0.0084)	(0.0870)	(0.1331)
Rock	0.0000	0.2198	-1.3036	-0.8878	-1.8685	-1.1150
	(1.3052)	(0.0174)	(0.0142)	(0.0085)	(0.0473)	(0.0634)
Urban	0.1839	-0.0731	-0.5809	0.1337	3.5947	0.3526
	(2.6119)	(0.0068)	(0.0408)	(0.0146)	(0.1306)	(0.0880)
News	0.3249	1.6597	2.2926	-0.5445	-0.5504	-1.4128
	(1.0074)	(0.0190)	(0.0180)	(0.0062)	(0.0460)	(0.0557)
Other Music	0.0001	1.2660	2.3363	-0.0195	0.3574	-1.0140
	(1.5411)	(0.0129)	(0.0149)	(0.0037)	(0.0633)	(0.0951)
Religious	0.0006	0.8060	0.9891	0.4884	1.4627	-0.7644
	(0.9300)	(0.0073)	(0.0112)	(0.0050)	(0.0718)	(0.1085)
Spanish	0.5654	0.4935	0.3341	0.0016	-0.4913	4.2042
	(0.8850)	(0.0378)	(0.0318)	(0.0149)	(0.0556)	(0.0947)
Constant (commercial radio)	0.1159		-	-	-	-
	(1.7724)					

			Station		Quality Transition	
	AM x Band		Character.		Specification A	Specification B
Adult Contemporary	-0.3549	Signal	1.0620	*Stations Remaining in Format*		
	(0.1858)	coverage	(0.1333)	ρ_1^ξ	0.8715	0.8792
CHR/Top 40	-0.5900	FM x	0.3168		(0.0044)	(0.0044)
	(0.2836)	coverage	(0.1439)	Second period mean change for switchers		0.0942
Country	-0.8341	Unlisted	-1.0170			(0.0127)
	(0.1483)	station	(0.0652)			
Oldies	-0.9500	Out of market	-0.6503	*Stations Switching Format*		
	(0.1733)	station	(0.1157)	ρ_2^ξ	0.7022	0.7067
Rock	-1.1905	FM x	4.8269		(0.0090)	(0.0168)
	(0.1892)	transm power	(7.9842)	μ_2^ξ	-0.0543	-0.0453
Urban	-1.1037	AM x	1313.5612		(0.1076)	(0.1082)
	(0.1593)	transm power	(213.7973)			
News	-0.6000	FM x	13.7148			
	(0.1402)	transm height	(47.0044)			
Other Music	-0.8331	Station age	-9.2514			
	(0.1396)		(49.0453)	Observations	42,858	42,858
Religious	-0.9064			GMM Objective	1206.8	1202.3
	(0.1471)			DoF: 756, 99% critical value: 851.5		
Spanish	-1.2485					
	(0.1499)					

Note: Standard errors in parentheses. Coefficients on time and market-format dummies not reported. Nonlinear, AM x Band and station characteristic coefficients reported from quality transition specification A, but these coefficients are almost identical using specification B.

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

	Data		Simulation
Switching Stations			
(Obs: 1,514)			
Mean Change in Share (Percentage point x10)	0.376		0.358
Standard Deviation (Percentage point x10)	2.245		2.852
Correlation for Individual Stations			
1 simulation		0.358	
Mean of 20 simulations		0.561	
Non-Switching Stations			
(Obs: 38,865)			
Mean Change in Share (Percentage point x10)	-0.011		0.018
Standard Deviation (Percentage point x10)	1.674		2.192
Correlation for Individual Stations			
1 simulation		0.052	
Mean of 20 simulations		0.142	

Table 8: Revenue Function Estimates

	(1)	(2)	(3)	(4)
Demographics				
Female	0.1588	0.1792	0.1529	0.1098
	(0.0194)	(0.0200)	(0.0197)	(0.0209)
Age 12-24	-0.4914	-0.4811	-0.5202	-0.5554
	(0.0274)	(0.0281)	(0.0270)	(0.0272)
Age 50+	-0.4610	-0.4590	-0.4502	-0.4732
	(0.0183)	(0.0184)	(0.0181)	(0.0188)
Black	-0.2604	-0.2679	-0.2529	-0.2446
	(0.0113)	(0.0116)	(0.0112)	(0.0109)
Hispanic	-0.1880	-0.1975	-0.1710	-0.1589
	(0.0119)	(0.0129)	(0.0131)	(0.0129)
Station Characteristics and Competition				
Number of stations commonly	-	0.0187	0.0148	0.0154
owned in format		(0.0042)	(0.0041)	(0.0042)
Number of stations owned	-	-0.0019	-0.0009	0.0004
by other firms in format		(0.0017)	(0.0017)	(0.0017)
Format switch in previous two	-	-0.1422	-0.1237	-0.1211
quarters		(0.0124)	(0.0127)	(0.0128)
Non-linear Revenue Effects				
Station market share	-	-	7.7194	7.4543
less market average			(0.6229)	(0.6229)
Proportion of station's audience in	-	-	-	-0.2520
demographic group				(0.0447)
Observations (station-year)	13,007	13,007	13,007	13,007
R^2	0.260	0.267	0.278	0.281
Measures of Fit				
Change in Revenue for Non-Switchers ($k)				
actual mean (std dev)	188 (1048)	188 (1048)	188 (1048)	188 (1048)
predicted mean (std dev)	120 (1081)	137 (1099)	137 (1153)	137 (1155)
correlation of actual, predicted	0.40	0.40	0.39	0.40
Change in Revenue for Switchers ($k)				
actual mean, std	140 (998)	140 (998)	140 (998)	140 (998)
predicted mean, std	320 (1672)	58 (1494)	92 (1505)	95 (1504)
correlation of actual predicted	0.58	0.52	0.55	0.56

Note: Estimation by Non-Linear Least Squares. Standard errors in parentheses are corrected for estimation error in the demand estimates by expressing as a GMM problem.
Specifications include market-year fixed effects.

Table 9: Estimated Multinomial Logit Model for Conditional Choice Probabilities

	Demographics and Mkt-Format Attractiveness				
	Proportion Hispanic	Δ Proportion Hispanic	Proportion Black	Δ Proportion Black	Estimated Mkt-Format Quality
Dark	-	-	-	-	-
AC	-1.182	-14.329	-0.258	-121.567	0.106
	(0.729)	(20.941)	(1.033)	(45.891)	(0.204)
CHR	-0.789	15.606	0.296	-83.262	0.051
	(0.863)	(22.586)	(1.128)	(49.974)	(0.193)
Country	-0.676	7.838	0.063	-39.356	-0.055
	(0.842)	(22.913)	(1.085)	(49.499)	(0.196)
Oldies	-0.765	-12.535	0.328	-115.425	0.180
	(0.906)	(25.150)	(1.143)	(52.507)	(0.177)
Rock	-1.113	0.676	-2.123	-52.334	0.244
	(0.823)	(20.849)	(1.089)	(46.518)	(0.217)
Urban	0.545	13.639	9.613	-94.205	0.349
	(0.818)	(24.191)	(1.761)	(50.458)	(0.133)
News	-0.478	4.686	0.354	-79.623	0.192
	(0.781)	(21.250)	(1.150)	(49.865)	(0.190)
Other M	-1.448	14.097	0.516	-93.743	-0.060
	(0.781)	(22.127)	(1.146)	(50.283)	(0.110)
Religion	-0.717	-42.715	3.500	-23.511	0.137
	(0.870)	(25.853)	(1.612)	(58.553)	(0.152)
Spanish	4.455	102.098	2.095	-84.457	0.469
	(1.409)	(21.506)	(1.308)	(58.522)	(0.091)

	Competition Variables			
	Number of stations in format	Combined share of other stations	Combined fixed quality of other stations	Combined ξ of other stations
Dark	-	-	-	-
AC	-0.137	-2.147	-0.022	-0.081
	(0.062)	(14.131)	(0.064)	(0.046)
CHR	-0.288	27.145	-0.014	-0.143
	(0.094)	(19.235)	(0.097)	(0.086)
Country	-0.203	24.348	-0.028	-0.065
	(0.074)	(12.466)	(0.054)	(0.043)
Oldies	-0.013	-48.236	0.010	-0.149
	(0.139)	(33.648)	(0.101)	(0.099)
Rock	-0.068	-11.125	0.069	-0.035
	(0.048)	(14.328)	(0.059)	(0.045)
Urban	0.070	-46.443	0.157	0.034
	(0.062)	(15.383)	(0.070)	(0.061)
News	-0.109	1.356	0.028	-0.033
	(0.062)	(15.633)	(0.048)	(0.041)
Other M	-0.054	14.324	-0.060	-0.047
	(0.074)	(18.360)	(0.052)	(0.047)
Religion	0.014	-88.928	0.060	0.068
	(0.099)	(43.376)	(0.071)	(0.083)
Spanish	0.139	-72.570	0.161	0.044
	(0.073)	(25.917)	(0.048)	(0.055)

Biggest station in format x stay	0.422	Current share x switch to dark	-926.667
	(0.0956)		(305.9957)
Current share x switch	-167.559		
	(16.1142)		

continues over....

Table 9 cont.

Switch Variables

	Stay x FM	Stay x AM	Switch x FM	Switch x AM
Dark	4.414	3.852	-	-
	(0.431)	(0.441)		
AC	6.509	5.999	2.895	-0.107
	(1.539)	(1.573)	(1.528)	(1.560)
CHR	4.935	3.889	1.359	-1.840
	(1.147)	(1.287)	(1.141)	(1.182)
Country	4.925	4.263	0.204	-0.584
	(1.338)	(1.337)	(1.317)	(1.329)
Oldies	6.282	6.091	2.179	1.031
	(1.335)	(1.328)	(1.324)	(1.319)
Rock	7.417	5.164	3.393	0.508
	(1.325)	(1.348)	(1.307)	(1.336)
Urban	6.135	6.137	2.075	0.460
	(1.027)	(1.050)	(1.016)	(1.044)
News	6.995	7.134	1.302	3.118
	(1.567)	(1.547)	(1.532)	(1.531)
Other M	4.001	3.741	-0.331	0.076
	(0.967)	(0.956)	(0.955)	(0.954)
Religion	6.820	6.727	0.797	1.029
	(1.299)	(1.270)	(1.275)	(1.278)
Spanish	8.236	7.763	2.592	2.455
	(0.906)	(0.876)	(0.858)	(0.877)

Switch x Mkt Pop

200k-500k	500k-1m	1m-2m	2m-4m	4m+
0.029	0.040	-0.218	-0.339	-0.417
(0.029)	(0.098)	(0.100)	(0.112)	(0.156)

Ownership Variables & Miscellaneous Variables

	Number stations commonly owned nationwide
Dark	-
AC	0.005
	(0.002)
CHR	0.013
	(0.003)
Country	0.008
	(0.002)
Oldies	0.011
	(0.005)
Rock	0.006
	(0.002)
Urban	0.015
	(0.006)
News	0.009
	(0.002)
Other M	0.010
	(0.007)
Religion	0.034
	(0.012)
Spanish	0.046
	(0.010)

Recent ownership switch	0.058
	(0.081)
Number owned in current market-format x stay	-0.079
	(0.048)
Number owned in alternative market format x switch	0.124
	(0.050)
Stations commonly owned by other firms in current format x stay	0.025
	(0.067)
Stations commonly owned by other firms in alternative format x switch	0.053
	(0.059)
Recent Format Switch x switch	0.058
	(0.081)
Number of observations:	41,539
Log-Likelihood:	-9344.0

Note: Estimation by Maximum Likelihood. Standard errors in parentheses are corrected for estimation error in the demand estimates by expressing as a GMM problem.

Table 10(a): Second Stage Parameter Estimates - Sunk Repositioning Costs

	Market Size					
	Population > 5 million (LA and Chicago)	Population 3-5 million (Seattle-Dallas)	Population 1-3 million (Portland, OR -Memphis)	Population 500k-1m (Little Rock-Buffalo)	Population 250k-500k (Macon,GA -Columbia, SC)	Population <250k (Casper, WY to Monroe, LA)
Annual Station Revenues in 2004, $m						
Mean	18.1	10.6	4.5	1.9	1.1	0.6
Maximum	60.3	45.5	28.2	12.0	7.0	4.1
Parameter Estimates, $m						
Sunk Repositioning Costs (θ_1)	[0.73, 81.67]	[6.35, 47.03]	[0.67, 13.75]	[0.10, 10.31]	[0.05, 2.38]	[0.15, 2.88]
95% CI	[0.03, 190.54]	[0.993 94.72]	[0.07, 39.33]	[-0.19, 19.30]	[-0.10, 9.05]	[0.06, 5.22]
Fixed Costs of Active Stations (θ_2)	[0, 11.93]	[0, 6.89]	[0, 2.89]	[0, 1.63]	[0, 0.58]	[0, 0.54]
95% CI	[0, 15.83]	[0, 8.50]	[0, 3.43]	[0, 1.75]	[0, 0.88]	[0, 0.60]
Scale of ε (σ)	[0, 12.20]	[0, 4.69]	[0, 1.79]	[0, 1.53]	[0, 0.31]	[0, 0.36]
95% CI	[0, 27.53]	[0, 10.66]	[0, 6.08]	[0, 2.96]	[0, 1.21]	[0, 0.74]
Number of Station Observations Used in Second Stage Estimation (Fall 2004)	90	233	676	459	489	473
Number of Markets	2	7	24	17	22	28
Costs of Observed Switching 1997-2006, $m						
Average Foregone Commercial Revenues in Year Following Switch	1.9	1.4	0.4	0.2	0.08	0.05
Average Sunk Repositioning Cost Paid (εs interpreted as heterogeneity in switching costs)						
Lower bound	0.73	6.35	0.67	0.10	0.05	0.15
Upper bound	11.54	20.25	3.69	1.95	0.70	0.89
Total Sunk Repositioning Costs Spent 1997-2006 at Upper Bound	727.0	2,409.8	1,778.5	776.1	266.7	285.7

Notes: $ numbers calculated using estimated value of listeners in 2004 for each market. Bounds and conservative confidence intervals calculated using the methods proposed by Pakes et al. (2006). Parameters assumed to be the same for all stations within a market size group.

Table 10(b): Alternative Estimates of Sunk Format Switching Costs
Excluding the Post-Switch Increase in Quality (Demand Specification A)

	Population > 5 million (LA and Chicago)	Population 3-5 million (Seattle-Dallas)	Population 1-3 million (Portland, OR -Memphis)	Population 500k-1m (Little Rock-Buffalo)	Population 250k-500k (Macon,GA -Columbia, SC)	Population <250k (Casper, WY to Monroe, LA)
Sunk Repositioning Costs (θ_1)	[-4.29, 73.57]	[3.08, 39.04]	[-0.54, 11.06]	[-0.50, 9.13]	[-0.28, 2.42]	[-0.04, 2.75]
95% CI	[-7.11, 171.63]	[-0.02 78.50]	[-1.08, 32.79]	[-0.72, 18.69]	[-0.44, 7.93]	[-0.13, 5.35]
Fixed Costs of Active Stations (θ_2)	[0, 11.49]	[0, 6.02]	[0, 2.46]	[0, 1.53]	[0, 0.68]	[0, 0.52]
95% CI	[0, 21.6]	[0, 7.79]	[0, 3.22]	[0, 1.63]	[0, 0.89]	[0, 0.58]
Scale of ε (σ)	[0, 11.39]	[0, 3.98]	[0, 1.54]	[0, 1.41]	[0, 0.36]	[0, 0.36]
95% CI	[0, 39.61]	[0, 9.28]	[0, 5.58]	[0, 2.82]	[0, 1.19]	[0, 0.75]
Average Sunk Repositioning Cost Paid						
Lower bound	-4.29	3.08	-0.54	-0.50	-0.28	-0.04
Upper bound	7.99	16.24	2.42	1.40	0.48	0.77

Notes: same as above.

Table 11: Effects of Format Switching 1997-2006 on Station Revenues and Listeners

	Market Size					
	Population > 5 million (LA and Chicago)	Population 3-5 million (Seattle-Dallas)	Population 1-3 million (Portland, OR-Memphis)	Population 500k-1million (Little Rock-Buffalo)	Population 250k-500k Macon, GA-Columbia, SC)	Population <250k (Casper, WY-Monroe, LA)
Change in Time Spent Listening Due to Format Switching 1997-2006, %						
White	-5.1%	-5.0%	-3.1%	1.7%	3.3%	4.5%
	(4.61%)	(1.99%)	(2.39%)	(2.85%)	(3.11%)	(3.22%)
Black	5.8%	18.6%	23.6%	32.5%	9.9%	29.1%
	(5.38%)	(7.31%)	(5.39%)	(7.62%)	(5.75%)	(10.33%)
Hispanic	20.7%	26.1%	63.1%	55.6%	39.7%	20.6%
	(5.92%)	(13.60%)	(14.35%)	(12.57%)	(12.15%)	(8.14%)
Aged 12-24	10.9%	3.9%	14.8%	21.1%	10.6%	22.9%
	(4.95%)	(3.26%)	(3.26%)	(3.52%)	(3.42%)	(5.92%)
Aged 25-49	5.6%	4.3%	6.3%	11.3%	6.6%	10.4%
	(4.68%)	(2.79%)	(2.67%)	(2.94%)	(3.11%)	(3.60%)
Aged 50+	-3.1%	-1.1%	-3.4%	-5.2%	0.8%	-1.6%
	(4.88%)	(2.38%)	(2.77%)	(2.96%)	(3.34%)	(3.59%)
Women	4.6%	1.8%	4.7%	5.0%	5.7%	4.5%
	(4.82%)	(2.63%)	(2.70%)	(3.13%)	(3.35%)	(3.40%)
Total	3.4%	2.4%	4.3%	6.7%	5.1%	7.6%
	(4.51%)	(2.61%)	(2.63%)	(3.00%)	(3.14%)	(3.46%)
Change in Per Period Revenues Due to Format Switching 1997-2006, $m						
Stations switching between active formats						
per station	0.51	0.30	0.04	0.05	0.02	0.00
	(2.01)	(0.85)	(0.26)	(0.10)	(0.11)	(0.05)
total	17.50	19.07	9.21	10.20	3.34	-0.45
	(68.26)	(53.39)	(66.28)	(18.55)	(21.96)	(8.14)
Stations switching from Dark						
per station	1.66	1.50	0.89	0.71	0.45	0.20
	(0.33)	(0.57)	(0.19)	(0.10)	(0.07)	(0.04)
total	1.66	7.49	34.59	19.14	12.48	9.66
	(0.33)	(2.84)	(7.38)	(2.61)	(1.82)	(1.87)
Stations remaining in the same active format						
per station	-0.04	-0.02	0.00	-0.01	-0.01	0.00
	(0.28)	(0.08)	(0.04)	(0.01)	(0.03)	(0.01)
total	-1.94	-3.44	-1.27	-3.08	-2.10	-0.98
	(15.20)	(13.07)	(14.13)	(3.00)	(8.38)	(2.03)

Notes: Standard deviations from using 50 simulation draws from the distribution of the first stage parameters in parentheses.

Figure 1: Market Shares of Switching Stations
(share in period prior to switch normalized to zero)

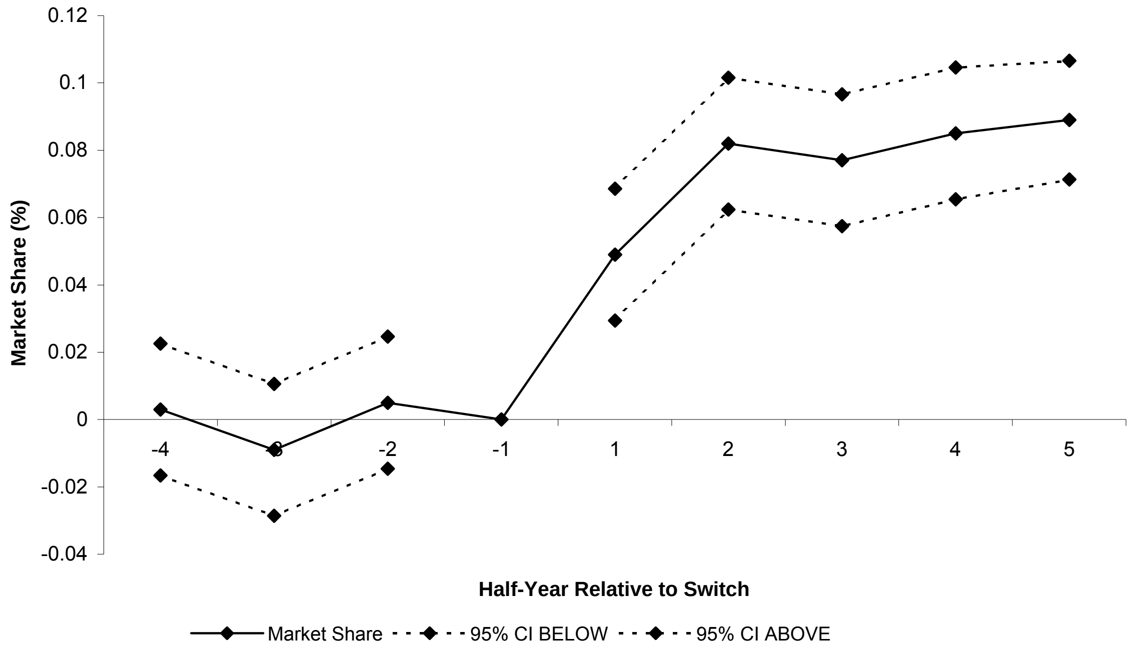


Figure 2: Distribution of Share Changes and Its Relationship With Format Switching

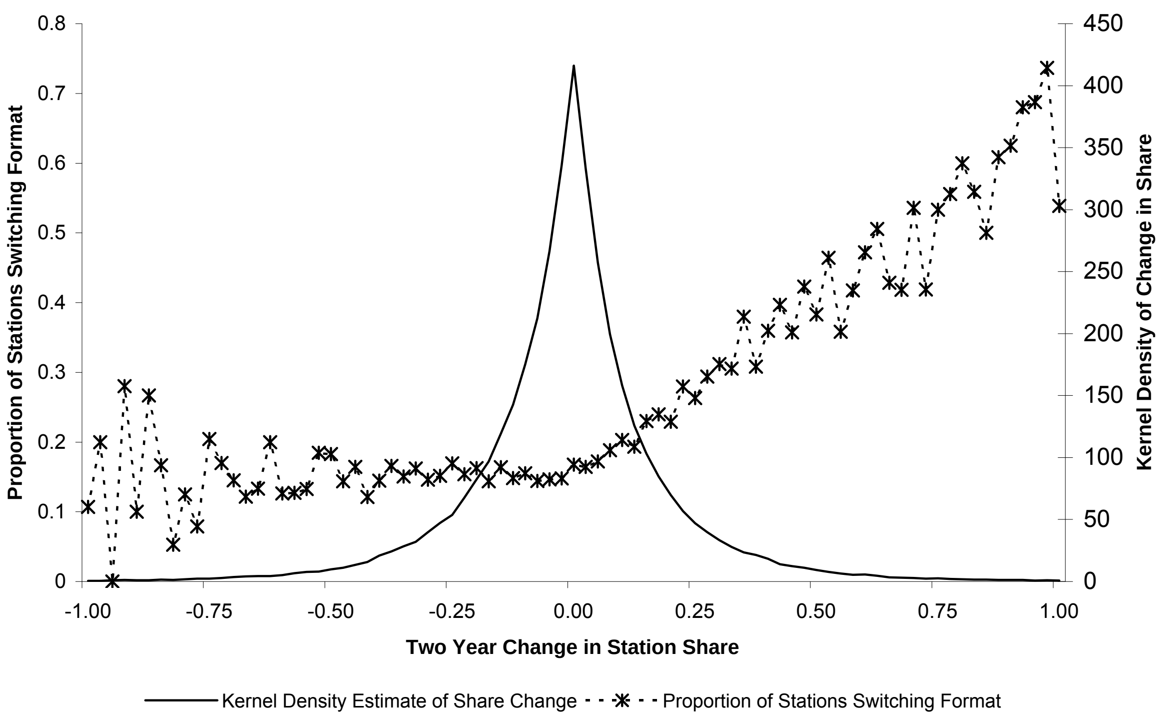


Figure 3(a): Relationship Between Switching Rate and Average Number of Listeners Per Station
(Number of listeners per station is almost perfectly correlated with market population)

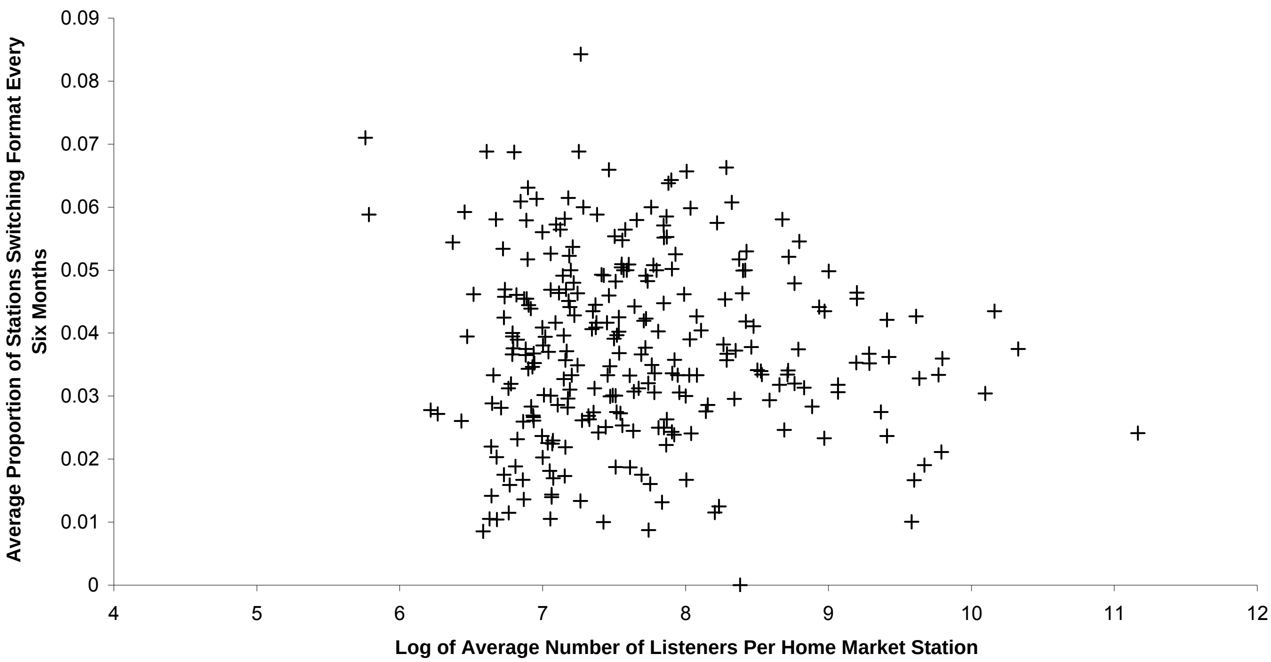


Figure 3(b): Market Shares of Switching Stations By Market Size
(Share in period prior to switch normalized to zero)

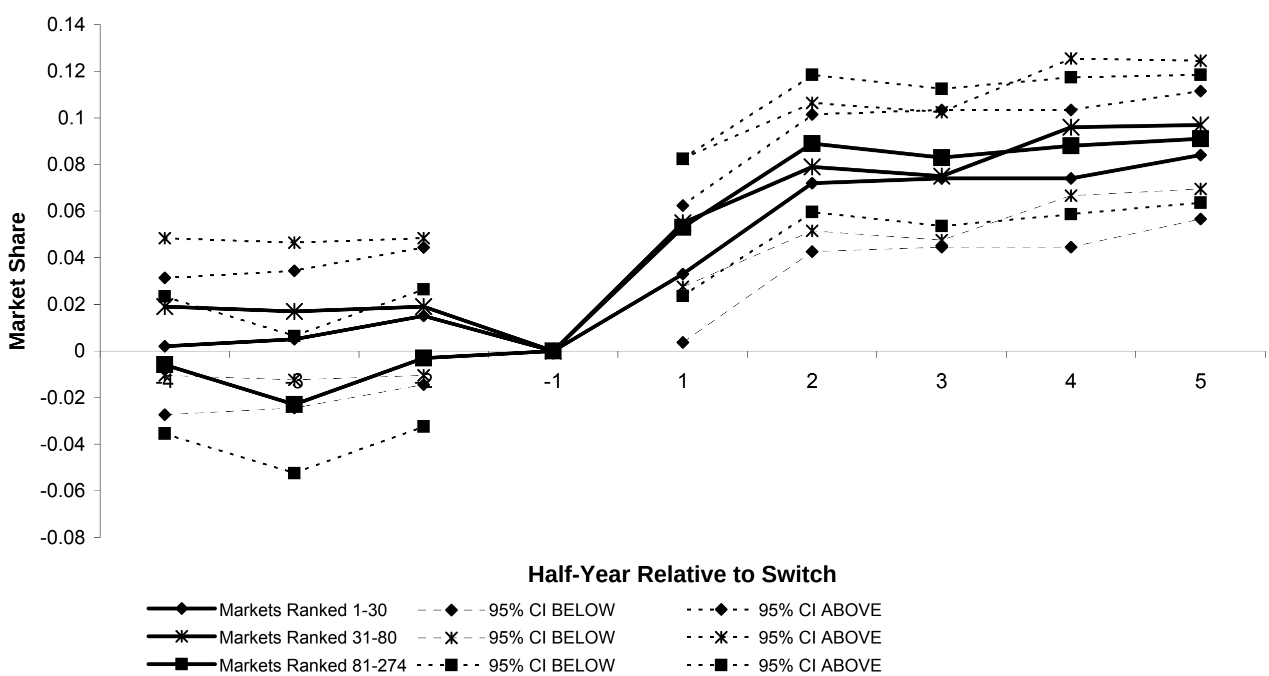


Figure 4(a): Bounds on Switching Costs Corresponding to Inequalities (28) and (29)

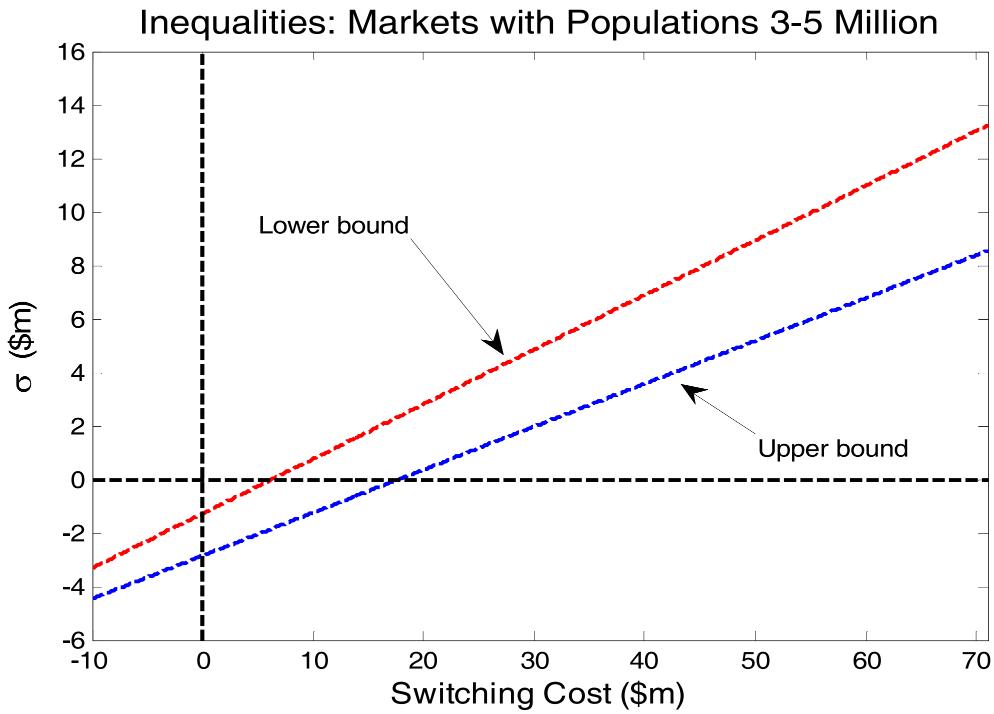


Figure 4(b): Bounds on Switching Costs Corresponding to Inequalities (28), (29) and (30)

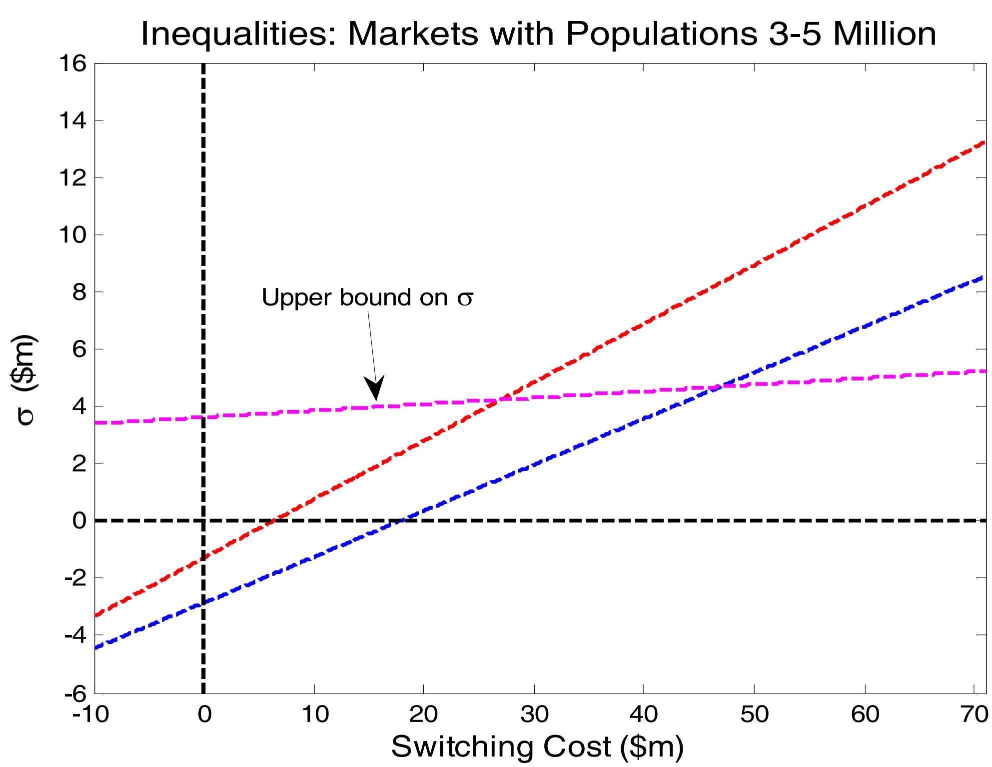


Figure 5: Bounds in Other Market Groups

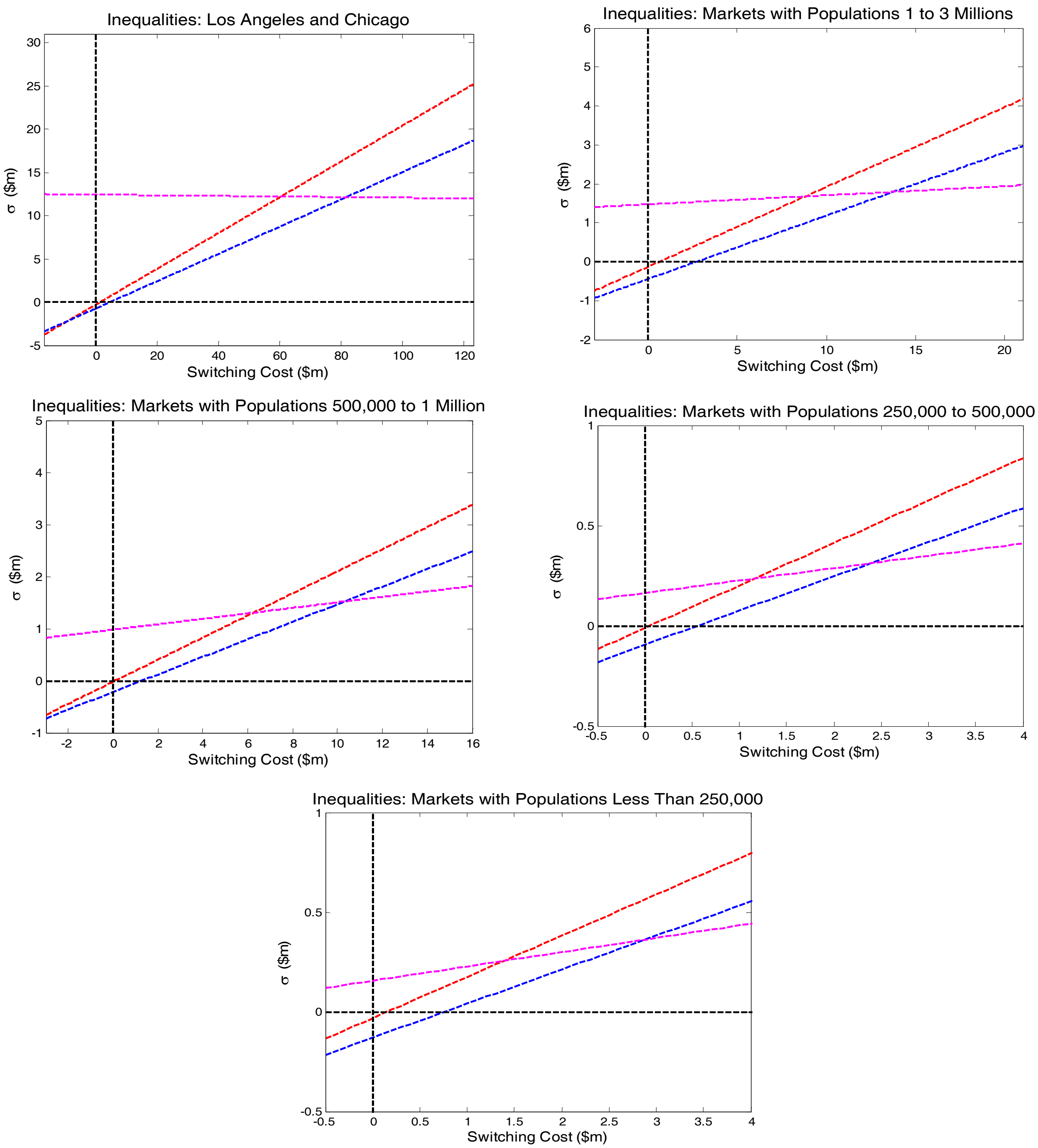
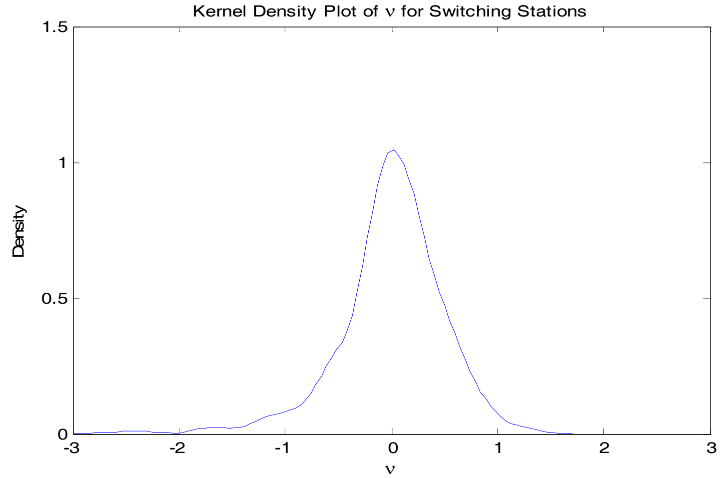


Figure 6(a) and (b): Innovations in Station Quality



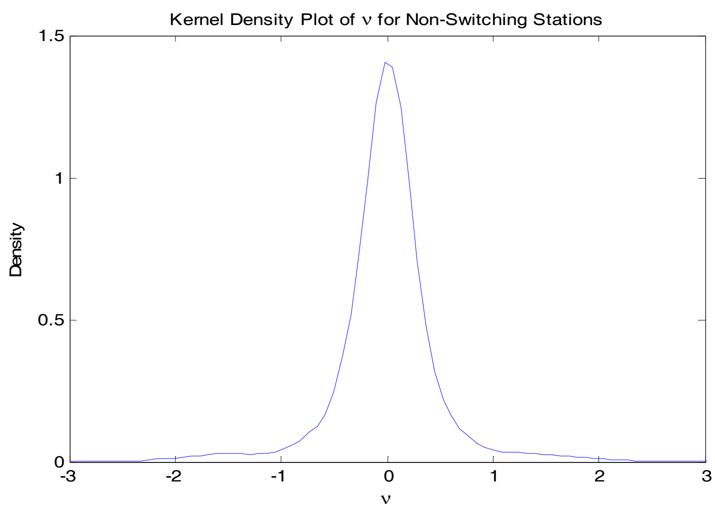


Figure 6(c): Empirical Distribution of Unobserved Station Qualities

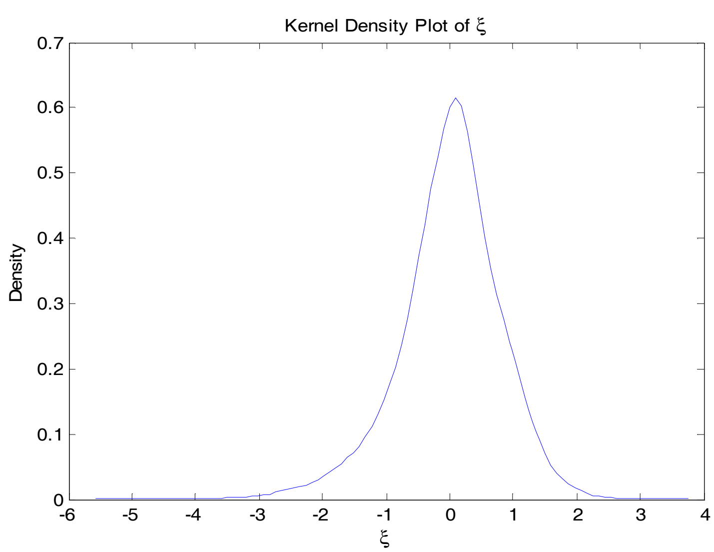
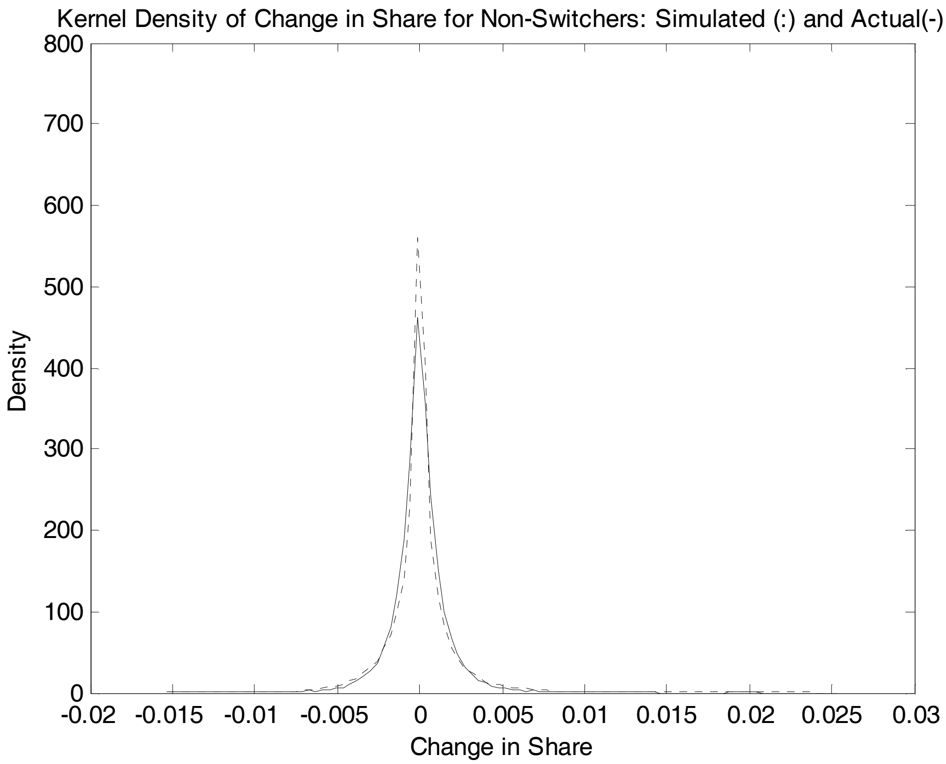


Figure 7: Simulated vs. Actual Changes in Share for Switching and Non-Switching Stations



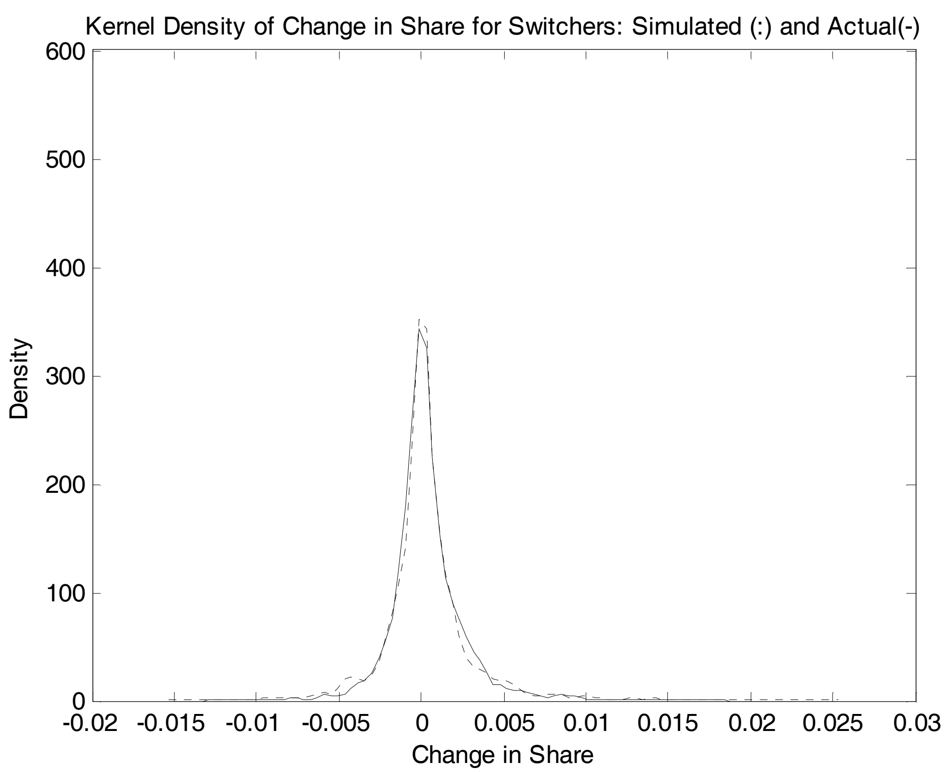


Figure 8: Distribution of Changes in Revenues for Stations Remaining in the Same Format 1997-2006
Markets with Populations Between 3 and 5 Million

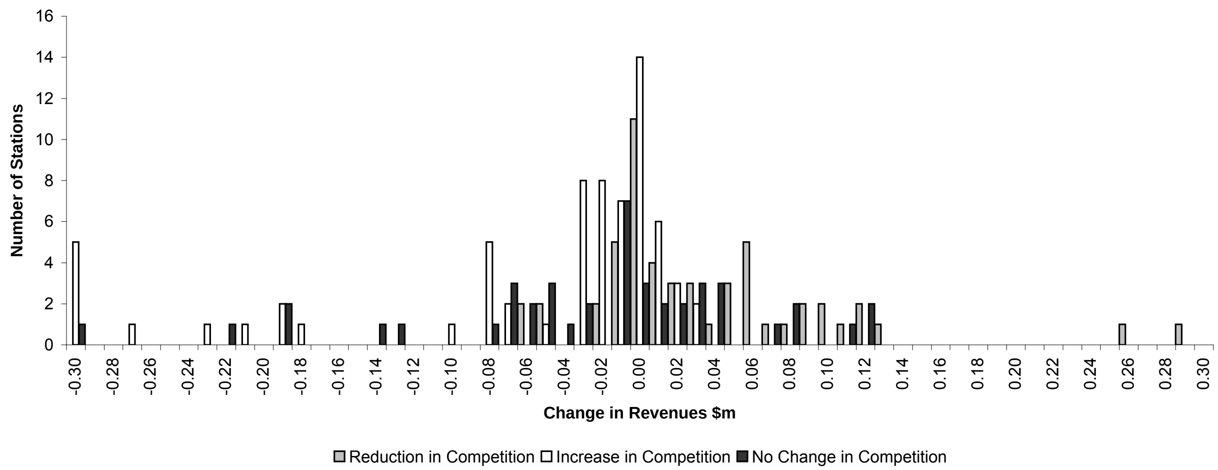


Figure 9: Number of Urban Stations in Minneapolis-St. Paul After A Positive Shock to the Black Population (100 Simulations)