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

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Abstract

This paper estimates a dynamic model of product repositioning in differentiated product markets using data from the broadcast radio industry. The feasibility of repositioning can play an important role in determining the medium and long-run effects of demand shocks, mergers and many kinds of policy intervention. The paper extends techniques for estimating dynamic oligopoly models to a setting with rich product differentiation and uses timing assumptions to consistently estimate demand allowing for the endogeneity of product characteristics. Repositioning (format switching) costs are found to be relatively small (less than one year's revenues for the average station) so that product selections change quite quickly in response to demand shocks. They increase with market size, consistent with stations spending resources to find new listeners and advertisers.

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1 Introduction

Most analyses of differentiated product markets treat the set of available products as given. While this may be appropriate for analyzing the effects of demand or policy changes in the very short-run, it may miss important medium and long-run effects if it is not prohibitively expensive for firms to change the products that they offer. For example, the effects of rising gas prices or policies designed to reduce carbon emissions on the automobile industry will depend on how difficult it is for American manufacturers to introduce more fuel efficient models (Berry et al. (1993)). Horizontal mergers provide another example. As recognized by the *Horizontal Merger Guidelines*, the market power of merging firms may be constrained by the threat that price increases would induce entry or repositioning by competitors even if the scope for demand substitution is limited. The feasibility of "supply-side substitution" (repositioning) in response to moderate price increases has been a key issue in the analysis of mergers in industries as diverse as radio, fountain pens, chewing tobacco and (currently) organic supermarkets.[1] However, despite evidence that there are significant supply-side responses to mergers (Berger et al. (2004)), the dynamics of product repositioning have received very little previous attention.

This paper estimates how costly it is for firms to reposition their products using the example of format switching in the broadcast radio industry. As should be obvious from the previous example, it is the level and distribution of entry and repositioning costs which determine how markets respond to different types of shock. Using a rich dynamic model I show that repositioning costs in the radio industry are less than one year's revenues for the average station and that, as a result, the set of available formats changes quite quickly in response to shocks. This is illustrated using demand shocks caused by changes in ethnic/racial demographics.

A notable feature of the paper is that it is focused on repositioning by incumbents rather than

[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)

entry by new firms. While spectrum constraints make entry unusually rare in the radio industry, repositioning is also the margin where one would expect most of the action to take place in markets with scale and scope economies (such as automobiles) or in the relatively short time horizons (1-2 years) considered in mergers.[2]

There are several reasons why the radio industry is an excellent place to study repositioning costs. Formats provide a well accepted and discrete measure of positioning which allow the application of techniques for estimating dynamic discrete choice models. The absence of technological barriers to repositioning makes it natural to consider stations as always being able to switch subject to paying a repositioning cost. However, the most important advantages concern the available data. I observe several thousand stations in discrete local radio markets, so that there are many examples of repositioning even though the per station-quarter rate of format switching is low. In addition, exogenous drivers of repositioning, such as demographic changes, are observable. Exogenous variation in market size also helps to identify some important characteristics of repositioning costs. Some types of cost, such as the need to replace a station's music library, should be the same across stations with different numbers of listeners. If these were the most important types of cost then we would expect to see more switching in larger markets, where revenues are higher, and this might lead one to favor a more relaxed merger policy in these markets as there would be more scope for supply-side substitution. On other hand, the costs of finding new listeners or advertisers might increase with market size, so that there might no more repositioning in larger markets. My results suggest that these latter types of costs tend to be more important.

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 studies of the effects of radio station ownership on

[2] Recent research (Bernard et al. 2006) across all manufacturing industries suggests that changes in the products offered by existing firms explains a much larger proportion of changes in industry output than firm entry and exit.

product differentiation and listenership. Berry and Waldfogel (1999) estimate station entry costs in the radio industry using a static model to address the question of whether there is excess entry in the sense of Mankiw and Whinston (1986). Tyler Mooney (2006) shows that stations migrated to formats more valued by advertisers in the late 1990s. Romeo and Dick (2005) find that stations switching format tend to gain listeners.

While there has been no previous attempt to estimate repositioning costs in industries with horizontal product differentiation[3], there have been several attempts to estimate the qualitatively-similar migration costs of individuals or households faced by different labor market opportunities in different cities or regions (Kennan and Walker (2006), Bayer and Juessen (2006) and Gemici (2007)). My setting is more complicated than the migration setting because of the need to allow for competitive interactions between firms.

1.1.2 Estimation of Dynamic Oligopoly Models

A dynamic model is necessary to estimate repositioning costs as the rewards from repositioning are likely to accrue over a number of future periods during which there may be additional changes in demand or market structure. Several recent papers (Aguirregabiria and Mira (2006), Bajari et al. (2006), Berry et al. (2006) and Pesendorfer and Schmidt-Dengler (2006)) have proposed methodologies for estimating dynamic oligopoly discrete choice models with Markov Perfect Nash Equilibria. These approaches build on the insights of Hotz and Miller (1993) and Hotz et al. (1994) for estimating single-agent problems without solving for equilibrium policies at each step of estimation. The approach which I take is closest to that suggested by Bajari et al. (2006). I use a moment inequality estimator in the second step, using the approach suggested by Pakes et al. (2006).

Ryan (2005), Collard-Wexler (2005), Ryan and Tucker (2006), Beresteanu and Ellickson (2006) and Macieira (2006) have applied these techniques to industry data. Ryan (2005) and Collard-Wexler

[3] Hitsch (2006) analyzes product introduction and withdrawal decisions in the ready-to-eat cereal industry focusing on how firms learn about the level of demand. Collard-Wexler (2006) estimates a cost which concrete producers pay to move from being small to large producers. Macieira (2006) estimates a cost which supercomputer manufacturer's pay to introduce a faster machine.

(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.

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

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, and an application to the effects of demographic changes, are presented in Section 6. Section 7 concludes.

2 Data

The main data source is BIAfn's *MediaAccess Pro* database which contains data on station characteristics (formats, band, signal coverage etc.), station ownership, station ratings and BIAfn's own estimates of station and market advertising revenues.[6] I use data from the Spring and Fall quarters

[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 for the decay of a movie's appeal has a similar spirit.

[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*.

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

I use the ten format categories listed in Table 1 to categorize each station's programming. This is an aggregation of the 20 format categories used by BIAfn, combining those categories, such as Rock and Album Oriented Rock, which are both very similar in content and have similar listener demographics. One would assume that the costs of switching between these categories are small. The remaining formats clearly appeal to different demographic groups based on age, sex and ethnicity/race.[9] A "Dark" format is also used for stations which are off-air.

2.2 Geographic Markets and Demographic Data

Arbitron defines local radio markets for estimating station ratings and these markets are also used by the FCC and the Department of Justice. The summary statistics below are based on data from 274 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 radio markets are close enough so that stations are rated in more than one market creating the possibility of interactions between markets. To avoid keeping track of these interactions, I estimate the structural model using data from the 100 markets where in every quarter less than 6% of rated

[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.

[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 Arbtiron's 2005 market definitions which are changed rarely.

listening is to stations based in other markets.

2.3 Listenership and Revenue Data

Arbitron reports quarterly estimates of station listenership based on diaries completed by a sample of listeners. I use two types of station-level share data. The first type is 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] The second type of station-level share data is demographic-specific data for different age/sex groups in Spring 2006.

BIAfn reports annual estimates of station revenues. These revenue estimates are based on information reported to BIAfn by many stations, together with a proprietary formula used by BIAfn to impute missing data. The revenue estimates are used to estimate a function which allows repositioning costs to be estimated in dollars.

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 can help to identify repositioning costs and which motivate the structure of my model. The statistics are based on behavior of stations in their home markets.

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.

[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.

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, and contrary to what one would expect if there were lower costs of switching between more similar types of programming, there is no systematic pattern of greater switching among the contemporary music formats than between music and talk or Spanish.[12]

2. Format switchers stations gain significant listenership. Figure 1 shows what happens, on average, to a station's share when it switches formats. The market share is measured as a percentage of time available to people aged 12 and above during a broadcast week of Monday-Sunday 6 am-12 pm and in the figure it is normalized to zero in the quarter (-1) prior to the switch (the average switcher has a market share of 0.5%).[13] A station's share increases significantly in the year (2 quarters) following a switch and then flattens off.

I focus on horizontal product repositioning as the investment which stations can make to 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 distribution of changes in market shares over a two year period and the dashed line shows the proportion of stations changing format during that two year period for each level of share change. On average, 15% of stations change formats during a two year period but amongst the stations experiencing the largest increases in share, over 50% are format switchers. The diagram also shows that few format switchers experience significant decreases in share suggesting that there may be relatively little uncertainty about how a switching station will perform in its new format.

[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 and stations for which shares have to be imputed are excluded.

3. The rate of switching is similar in markets of different sizes. Figures 3 and 4 show that there is no systematic relationship between the rate of switching and the average number of listeners to each station in the market (which is very highly correlated with population) and that the average market share gain of switching stations is also similar across markets of different size.

One can form a rough estimate of the magnitude of switching costs using the average, observed share increase of format switchers. For example, suppose that the marginal switcher expects its market share to permanently increase by 0.08 percentage points if it switches with a fixed market population and a price per listener fixed at its average 2005 value. Assuming an annual discount rate of 10%, the following table lists the present discounted value of the share increases in five markets.

Market Name	12+ Population 2005 (millions)	Average Price Per Listener-Year 2005 ($)	Estimated PDV of Permanent 0.08 Percentage Point Increase in Listenership ($m)
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

The aim of using the structural model is to improve on these estimates by distinguishing between the expectations of the marginal and the average switcher and by more accurately capturing stations' expectations about future revenue changes.

4. Changes in market demographics and competition affect format switching. In my model format switching is driven by competition for listeners and changes in market demographics, in particular their ethnic/racial composition. Table 3 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 the format and the explanatory variables include ethnic/racial demographics and a measure of competition as measured by the market share achieved by stations based on in nearby markets. I instrument for the competition variable as explained in the notes beneath the table.[14]

The coefficients show the expected pattern. An increase in the black population leads to more Urban and Religious stations while an increase in the Hispanic population is associated with more Spanish stations. The competition coefficient is negative in most formats, and when the formats are pooled together the coefficient is negative and statistically significant.

4 Dynamic Model of Format Switching

This section describes the various components of the dynamic model of format switching.

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

[14] I create the instrument in the following way: I calculate the average (across quarters) share of listening in each market to stations which are home to every other market. I then find each station's average (across quarters) share of listening in its home market. I multiply these two numbers together to calculate the predicted share of each out of market station. I then add the predicted shares of all of the out of market stations in a category to create the instrument. This instrument implicitly assumes that an out of market station's choice of format does not depend on the number of home market stations in a format. This 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.

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, and only less than 50 examples of exit many of which were associated with FCC licence withdrawals after rule violations.[15]

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). Each market is also associated with a particular advertising price per listener and each format in each market has a particular attractiveness $\overline{\gamma_m^F}$ 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 quarter the timing of the game is as follows:

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

[15] 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 grow to exceed Arbitron's minimum reporting standards (about 0.3% of radio listening). The analyses in Berry and Waldfogel (1999 and 2001), which are based on Arbitron rated stations listed in *Duncan's American Radio* series, include these examples of station growth as cases of entry, which may be appropriate if the growth requires significant investment.

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

3. listeners choose which station to listen to based on current station qualities, formats and the attractiveness of each format and station listenership is translated into revenues by a function capturing the operation of the advertising market. Station payoffs (advertising revenues, switching costs, ε) for the current quarter are realized; and,

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

4.3 Static Station Payoffs

A station's payoff each quarter depends on its listenership, translated into dollars by a revenue function and its format switching choice. In the simplest specification, 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

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

The parameter θ is the repositioning cost associated with switching between different active formats. σ is the scale parameter for the payoff shocks which are assumed to be drawn from an extreme value (Gumbel) distribution with location parameter 0. One could think of the εs as reflecting heterogeneity in format switching costs and this interpretation, rather than one relating to a station's ability in different formats, is the one which is most consistent with the iid assumption which is required for tractability. σ is identified because the estimates of station revenues allow payoffs to be expressed in dollars.

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

$$u_{ismt} = \gamma_i^C + F_{smt}\gamma_{imt}^F + X_{sf_st}\gamma^S + \xi_{smt} + \varepsilon_{ist}^L \tag{2}$$

where F_{smt} is a row vector indicating the current format of station s and ε_{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 a stations in formats F and I assume that

$$\gamma_{imt}^F = \overline{\gamma_m^F} + \gamma_A^F A_i + \gamma_E^F E_i + \gamma_S^F S_i + \Gamma_{RC}^F v_i^F \tag{3}$$

$\overline{\gamma_m^F}$ 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 systematic correlations in preferences for stations in the same format in addition to those caused by demographics. As is standard in 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. Finally the ε_{ist}^Ls are the Type I extreme value idiosyncratic differences in the station preferences of individuals.

4.3.2 Revenue Function

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

$$R_{smdt} = \alpha_{my(t)}(1 + W_{smt}\alpha^W)(1 + D\alpha^D) + \varepsilon^R_{smt} \tag{4}$$

$\alpha_{my(t)}$ 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 the format and whether the station is commonly owned. I also allow an additional effect of a recent format switch on revenues, as stations may have to discount advertising prices to develop new relationships with advertisers.

4.4 Evolution of the State Space

There are three parts of the state space which evolve over time: station formats, unobserved station quality and market ethnic/racial demographics. Station formats evolve deterministically according to station choices. Quality and demographics evolve according to stationary AR(1) processes.

4.4.1 Unobserved Station Quality

I assume that unobserved station quality evolves according to

$$\xi_{smt} = \rho^\xi_1 \xi_{smt-1} + \nu_{1smt} \tag{5}$$

where $\nu_{1smt} \sim N(0, \eta^\xi_1)$ for stations remaining in the same format, and I assume that it evolves according to

$$\xi_{smt} = \rho^\xi_2 \xi_{smt-1} + \mu^\xi_2 + \nu_{2smt} \tag{6}$$

with $\nu_{2smt} \sim N(0, \eta_2^{\xi})$ for stations switching formats. This second transition process only applies in the quarter in which the station switches formats.[16]

4.4.2 Market Demographics

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

$$g_{emt} = \rho^e g_{emt-1} + \mu^e + \nu_{emt}^D \tag{7}$$

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

4.5 Equilibrium Concept: Markov-Perfect Nash Equilibrium

In common with the recent literature on dynamic oligopoly models, I assume that stations play a symmetric, anonymous, stationary, pure strategy Markov Perfect Nash Equilibrium.[17] Formally, a station's strategy ς_s is a function mapping from the observable state space and the station's own current payoff shocks (the ε_ss) to actions (format choices), i.e., $\varsigma_s : \mathcal{S}$ x $\varepsilon_s \rightarrow A_s$.

Station s's value function prior to the realization of its current ε_ss is

$$V_s(\mathcal{S}|\varsigma_s) = E_\varepsilon \left[\pi_s(\mathcal{S}, \varsigma_s(\mathcal{S}, \varepsilon_s)) + \beta \int V_s(\mathcal{S}'|\varsigma_s) dP(\mathcal{S}'|\varsigma(\mathcal{S}, \varepsilon), \mathcal{S}) \right] \tag{8}$$

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

[16] A simple structure for unobserved station quality is necessary as I need to be able to "back out" unobserved station quality from the estimates of listener demand. This would not be possible if one included multiple dimensions of unobserved quality.

[17] 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 of the state space.

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

$$V_s(\mathcal{S}|\varsigma_s^*, \varsigma_{-s}^*) \geq V_s(\mathcal{S}|\varsigma_s', \varsigma_{-s}^*) \ \ \forall \mathcal{S}, \varsigma_s' \tag{9}$$

Prior to the realization of the ε_ss (or to a researcher who does not observe the ε_ss) 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 as if they were individual payoff-maximizing firms.

5 Estimation

5.1 Road Map

I follow the literature in using a two-step estimation approach. Listener demand, station conditional choice probabilities (policies), the revenue function and transition processes are estimated consistently in the first step. In the second step the remaining parameters of the payoff function (format switching costs and σ) are estimated. This involves using forward simulation to calculate future station payoffs and then finding the parameters which make alternative 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 process governing unobserved station quality using a GMM procedure. The main difference to the approach of Berry et al. (1995) is that I use the assumptions on the timing of innovations in station quality to consistently estimate the demand parameters, allowing for the endogeneity of format choices.

5.2.1 Quasi-Differenced Demand Moments

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

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

where Γ^L are the linear 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., higher quality stations might select into Country in Knoxville, TN than Boston, MA).[18]

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

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

[18] 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.

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

$$\nu_{1smt} = \xi_{smt} - \rho_1^{\xi} \xi_{smt-1} \tag{12}$$

$$= (\delta_{smt} - \rho_1^{\xi} \delta_{smt-1}) - \left(\widetilde{X_{smt}} - \rho_1^{\xi} \widetilde{X_{smt-1}} \right) \Gamma^L \tag{13}$$

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

$$\nu_{2smt} = \xi_{smt} - \rho_2^{\xi} \xi_{smt-1} - \mu_2^{\xi} \tag{14}$$

$$= (\delta_{smt} - \rho_2^{\xi} \delta_{smt-1}) - \left(\widetilde{X_{smt}} - \rho_2^{\xi} \widetilde{X_{smt-1}} \right) \Gamma^L - \mu_2^{\xi} \tag{15}$$

The innovations can be used to form moment conditions

$$E[Z_{smt} \nu_{smt}(\Gamma, \rho^{\xi})] = 0 \tag{16}$$

where the Zs are instruments. Under my assumptions, all of the observed station characteristics, include formats at t and $t-1$ are valid instruments. Additional instruments, based on format x demographic and competition interactions, help to identify the non-linear taste parameters. 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.[19]

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 non-linear taste parameters.[20] 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

[19] 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, the sum of the proportion of market covered by the signals of other stations in the format and the proportion of blacks and Hispanics in the market population.

[20] 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 Aribtron ratings panel varies across from quarter-to-quarter.

defined below as suggested by Nevo (2000).[21] Finally, the innovations are calculated which 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 three sets of moments. The first set match the proportion of a station's audience in each of six age-sex specific demographic groups to those reported in the station-level Arbitron data for Spring 2006,

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

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

The station-level data does not contain information on ethnic or racial listening. However, the second set of moments match the average proportion of listeners who are black/Hispanic for stations in each format to those reported by Arbitron for Spring 2003, 2004 and 2005.

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

Z_{esmt} 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 third 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,

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

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

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

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

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.[22] 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 contain more than one quarter.[23]

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

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.

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

[23] Average revenues per listener are similar across markets of different sizes, whereas total revenues are much bigger in larger markets. Using total revenues therefore tends to give too much importance from observations from larger markets.

5.4 First Step: Conditional Choice Probabilities

The Markov Perfect Nash equilibrium assumption implies that equilibrium station conditional choice probabilities should be functions of the state variables. In an ideal world these should 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 conditional choice probabilities can be adequately approximated using a multinomial model where the explanatory variables are rich functions of the state variables as well as controls for the effects of ownership. This approach is also takes by Ryan (2006), 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 conditional choice probabilities and the revenue functions use estimates from the demand model. It is not feasible to estimate them 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 results in Pakes (1997).

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.

5.6 Second Step: Estimation of Repositioning Costs

The second step uses the first step estimates to estimate the remaining parameters, θ (repositioning costs) and σ (the distribution of payoff shocks). I use a moment inequality estimator based on the equilibrium restriction that a station's observed policy should yield higher expected payoffs than alternatives. The present value of the components of expected future payoffs (revenues, switching costs and future expected εs) are estimated using forward simulation.

Formally, equilibrium requires that

$$V_s(\mathcal{S}|\varsigma_s^*, \varsigma_{-s}^*, \theta) - V_s(\mathcal{S}|\varsigma_s', \varsigma_{-s}^*, \theta) \geq 0 \; \forall \mathcal{S}, \varsigma_s' \tag{17}$$

where

$$V_s(\mathcal{S}|\varsigma_s, \varsigma_{-s}^*, \theta) = E_{\varsigma_s, \varsigma_{-s}^*} \sum_{t=0}^{\infty} \beta^t R(L_{smt}(\mathcal{S}, \Gamma), \alpha) - \theta \left(E_{\varsigma_s, \varsigma_{-s}^*} \sum_{t=0}^{\infty} \beta^t I(f_{st} \neq f_{st+1}, f_{st+1} \neq 0) \right)$$
$$+ \sigma E_{\varsigma_s, \varsigma_{-s}^*} \sum_{t=0}^{\infty} \beta^t \varepsilon_{st}(f_{st+1})$$

and expectations are taken with respect to station strategies and possible future transitions for station qualities and market demographics. Denoting the three components of a station's expected payoffs under its actual policies as R_s^*, S_s^* and ε_s^* and under a particular alternative policy as R_s', S_s' and ε_s', the inequality can be written as

$$R_s^* - \theta S_s^* + \sigma \varepsilon_s^* \geq R_s' - \theta S_s' + \sigma \varepsilon_s'$$

In practice there is significant simulation error in estimating the component of these payoffs because of the several kinds of future uncertainty which need to be integrated over. One way to deal with this is to use many simulations per station observation (several hundred are needed in practice to get convergence), but it is also possible to take averages across station observations

$$\overline{R^*} - \theta \overline{S^*} + \sigma \overline{\varepsilon^*} \geq \overline{R'} - \theta \overline{S'} + \sigma \overline{\varepsilon'} \tag{18}$$

Re-arranging this inequality makes it straightforward to see how the parameters can be bounded by considering appropriate alternative policies.

$$\theta \geq \frac{(\overline{R'} - \overline{R^*})}{(\overline{S'} - \overline{S^*})} + \sigma \frac{(\overline{\varepsilon'} - \overline{\varepsilon^*})}{(\overline{S'} - \overline{S^*})} \text{ if } (\overline{S'} - \overline{S^*}) > 0 \tag{19}$$

$$\theta \leq \frac{(\overline{R'} - \overline{R^*})}{(\overline{S'} - \overline{S^*})} + \sigma \frac{(\overline{\varepsilon'} - \overline{\varepsilon^*})}{(\overline{S'} - \overline{S^*})} \text{ if } (\overline{S'} - \overline{S^*}) < 0 \tag{20}$$

$$\sigma \leq \frac{(\overline{R^*} - \overline{R'})}{(\overline{\varepsilon'} - \overline{\varepsilon^*})} + \theta \frac{(\overline{S'} - \overline{S^*})}{(\overline{\varepsilon'} - \overline{\varepsilon^*})} \text{ if } (\overline{\varepsilon'} - \overline{\varepsilon^*}) > 0 \tag{21}$$

Consider an alternative policy which increases the number of expected switches and increases expected future revenues. Then the fact that this policy is not chosen will provide a lower bound on the repositioning costs (inequality 19). I operationalize this alternative policy by reducing the probability that a station stays in the same format by 0.2 and scaling up proportionally the probability of choosing each alternative format except Dark (the station will therefore remain more likely to choose more attractive formats if it switches).[24]

On the other hand, consider an alternative policy which reduces expected future switching and also reduces revenues. Then the fact that this policy is not chosen will provide an upper bound on repositioning costs (inequality 20). I consider a very simple form of this alternative policy which has the station never switching formats.

The bounds (in θ, σ space) created by these two alternative policies are shown in Figure 5. These diagrams were created using data from all of the markets, under the assumptions that the parameters are the same across markets. The two bounds are upward sloping because policies which increase switching tend to increase the value of expected future εs, so that for higher values of σ repositioning costs must be larger to rationalize a station's actual policies.

Identification of repositioning costs therefore also requires an alternative policy which can be used

[24] In practice this alternative policy means doing the following during the forward simulations: in each quarter considered the conditional choice probabilities implied by the parameters of the multinomial logit (assumed to represent a station's actual policies) and the current values of the state variables are calculated for each station. Then for the station under consideration I reduce the probability that the station remains in its current format by 0.2 (if possible) and scale up the probabilities of each of the alternatives appropriately. These new probabilities are compared with the value of a draw from a $U[0, 1]$ distribution to find the station's action and the expected value of ε conditional on this chosen action. The actions of other stations are calculated using the (unaltered) conditional choice probabilities implied by the multinomial logit.

to provide an upper bound on σ by increasing the expected value of future εs and reducing expected revenues without increasing the number of expected future switches. An alternative policy which achieves this is to keep the probability of a station remaining in its current format the same as under its actual policy but then equalizing the probabilities of choosing alternative formats (except Dark). An example may be helpful in understanding the logic. Suppose that there are only three formats, Rock, Spanish and Urban. Consider a Rock station in a market with a large and growing Hispanic population and a very small and declining black population. Suppose that (based on these demographics) the estimated conditional choice probabilities (the station's actual policies) imply that the probability of it remaining in Rock is 0.7, of switching to Spanish is 0.25 and switching to Urban is 0.05. Given these probabilities, the expected value of the station's payoff shock if it chooses to switch to Spanish is 1.96σ and to Urban 3.57σ, with expected value if it switches equal to 2.23σ.[25] If the probabilities of switching to Urban and Spanish are equalized at 0.15, the expected payoff shock if the station chooses to switch increases to 2.47σ. The probability of switching remains unchanged and, as the probability of switching to an undesirable format (given market demographics) has increased, expected revenues should also fall. The resulting bound on σ using the actual data is shown in Figure 6, and it provides an upper bound on the dollar level of switching costs as well as on σ.

The procedure for estimating the bounds using the moment inequalities follows Pakes et al. (2006), although the linearity of the inequalities makes this straightforward. The procedures in Pakes et al. are also used to calculate confidence intervals.

6 Results

This section presents the results from estimating the structural model. I use data from the 100 markets where less than 6% of radio listening is to stations based in other markets so that I can safely ignore interactions between markets.

[25] The expected value of a Type I extreme value payoff shock associated with a selected choice is $0.577 - log(P)$where P is the probability of the choice being made prior to the shocks being realized.

I also make two additional adjustments to the data. First, there has been a slow decline in radio listening, at similar rates in nearly all markets, since the mid-1980s. Revenues per listener have also been increasing and since 2001 these trends have roughly offset each other so that total industry revenues, as reported on the Radio Advertising Bureau's website, have been fairly constant in real terms. Rather than modelling two trends which appear to be offsetting each other, I remove the national trend from the share data and assume that real revenues per listener will remain fixed in the future.

Second, I need to deal with stations which are too small to meet Arbitron's Minimum Reporting Standards (typically around 0.3% of radio listening) so that their shares are not reported. Around 25% of stations can having missing data in any quarter, although they represent a small share of total listening. To avoid imputing shares for a very large proportion of the sample, I drop stations which are missing data for over half of the quarters in the sample (17% of stations), and impute a share for the remainder based on how many quarters of data are missing and the share of the smallest station in the market-quarter which is listed by Arbitron (so that 6% of the remaining observations have imputed shares).

6.1 First Step: Listener Demand

Table 4 presents the estimated coefficients from the demand model and the processes governing station quality.[26] The demographic format taste parameters show the expected pattern (given the average format demographics in Table 1) and most of them are precisely estimated. The standard deviations of the random components of format tastes are mostly small and insignificantly different from zero. This finding is consistent with demographics capturing most of the differences in individuals' tastes for formats (rather than stations) within markets.[27]

The coefficients on the fixed station quality characteristics are sensible, with greater signal coverage

[26] 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.

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

and more powerful transmitters associated with higher 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 estimated to of higher quality in News than formats such as Rock and Urban as expected. However, the quality of AM stations in Adult Contemporary and Contemporary Hit Radio is also estimated to be high, even though there are few AM stations in these formats.

The final part of the table reports the coefficients controlling the evolution of unobserved station quality. The ρ^{ξ} parameters are both less than one so quality is stationary as assumed. Consistent with few format switchers seeing a large decline in listenership, the parameters suggest that quality is largely transferred across formats ($\rho_2^{\xi} = 0.71$) and that the innovations in quality for format switchers have only slightly greater variance than for stations remaining in the same format. Stations are estimated to experience a small but not significant decline in quality when they switch formats.

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

Figures 7(a)-(c) show the pdfs of the innovations in unobserved station quality (the residuals from the quasi-differenced moments) for switchers and non-switchers and of the quality itself. The innovations are close to normal distributions with slightly too much weight in both of the tails. Qualities also have a bell-shaped distribution with too much weight in the lower tail.

I can also compute how well the demand model and innovation processes do 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 8 compares the changes in share seen in the data with those simulated from the model. For both switchers and non-switchers the fit is very good except for a very small number of simulated share changes which are too large.

One can also calculate the model's performance at predicting changes for individual changes. To do this I calculate predicted changes by taking averages across 50 simulations of the innovations in quality for each station. The correlation between these predicted changes and the changes seen in the actual data for format switchers is 0.58. The correlation for stations remaining in the same format is lower, 0.15. This is not surprising as stations remaining in the same format are less affected than format switchers by the type of structural change in product positioning which the demand model is designed to address.

6.2 First Step: Revenue Function

The upper section of Table 5 reports the coefficients from several specifications of the revenue function. 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 patterns continue to hold in the other specifications. The bottom section 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 be looking to establish relationships with advertisers). Common ownership with an additional station in the format increases revenues per listener by 2%.[28] Competition reduces revenues by a small and barely significant amount (0.2%). The absence of a competition effect would be consistent with advertising prices being set in a broader advertising market. There is a large, direct effect of format

[28] 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.

switching on station revenues as prices per listener are estimated to fall by 14% in the year following the format switch. When these effects are included, the average increase in revenues for switchers is now underpredicted by almost \$100,000 (average revenues are \$4.1 million).

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 increase with audience sizes in local television. The third specification allows for prices to vary with the difference between the station's market share and the market average, and consistent with the Fisher et al. result prices per listener are increasing with station size. Including this effect moves the predicted change in revenues for switchers towards the observed change. The final specification allows prices per listener in each demographic to vary with the proportion of the station's listenership who are in that demographic. 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 why this should be the case and in using the revenue function below I use the results from the third specification.

6.3 First Step: Station Conditional Choice Probabilities

Table 6 reports the coefficients from the multinomial logit estimates of station policies. The first page of the table shows the coefficients on variables that one can think of as affecting the attractiveness of a format if the effects of competition are ignored. The pattern of coefficients is sensible. Large and growing Hispanic populations make stations more likely to choose the Spanish format, whereas large black populations make stations more likely to choose Urban and Religious. The growth in black population does not show up as statistically significant for these formats, probably because black growth shows less variation than Hispanic growth 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.[29]

[29] I have to do one piece of imputation here for the market-formats in which stations are never observed. This mainly affects the religious format in markets outside the south and the Spanish format in markets with few Hispanics. The current estimates assume that market-format attractiveness in these markets is equal to the 25% percentile of markets where the measures can be estimated. These results do not appear to be particularly sensitive to the percentile used.

The second page 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, larger stations are less likely to switch. The third page lists the 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 page 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 large 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 can 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 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.

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 structural model. The estimates are

$$g_{emt} = \underset{(0.057)}{0.863} g_{emt-1} + \underset{(0.000)}{0.002} + \nu^{D}_{emt} \tag{22}$$

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

6.5 Second Step Estimates: Repositioning Costs

I now present some preliminary estimates of repositioning costs using the moment inequality approach outlined above. The next version of this paper will include a comparison of these estimates with point identified estimates using moment equalities.

The first row of Table 7 shows the estimated bounds and associated confidence intervals when data from all markets are pooled together and I assume that the parameters (θ and σ) have the same dollar value in every market. The lower bound is just under \$0.5 million and the upper bound is over \$4.5 million dollars.

The stylized facts described in Section 3 strongly suggest that repositioning costs are different in markets of different sizes, possibly because the costs are caused by stations having to find new listeners and advertisers. The remaining rows of Table 7 therefore report estimates dividing the sample into three market size groups of small (population in 2005 less than 0.5 million), medium (population between 0.5 million and 2.4 million) and large (population more than 2.4 million) groups. Although repositioning costs of around \$1.5 million are inside the bounds in all markets, the upper bound estimates are clearly much larger in larger markets.

As mentioned in Section 4, one interpretation of the payoff shocks is that they represent heterogeneity in payoff switching costs. As in Figure 6, the upper bound estimates of θ are associated with positive values of σ. This implies that the repositioning costs of stations choosing to switch formats ($\theta - \sigma\varepsilon$) will likely be less than θ and it is these repositioning costs which are more important for calculating the welfare costs of format switching. The final column of Table 7 reports the expected repositioning costs of switchers at the upper bound estimates of θ.[30] The new estimates are substantially lower than the upper bound estimates of θ for three three groups of markets.

The plausibility of the estimated repositioning costs of switchers can be assessed by comparing them with the back of the envelope estimates reported in Section 3. The structural estimates have a similar order of magnitude but are lower than the ballpark estimates, particularly in larger markets. This is what one would expect as the ballpark estimates assumed that the marginal switcher had the same expected share gain as the average switcher (we would expect it to be lower) and assumed that the initial share gain of switchers would be permanent (whereas it seems plausible that it might tend to erode over time).

6.6 An Application: Repositioning Following Demand Shocks

Waldfogel (2003, 2004) shows that, in industries with significant entry costs, a person with distinctive preferences will have more products designed to attract her in markets where more people share her tastes. Waldfogel (2003) illustrates this point using data from a cross-section of radio markets where there are more black-oriented (Urban and Religious) stations in markets with larger black populations and more Spanish stations in markets with more Hispanics. I now apply my model to examine (i) how quickly repositioning will take place if the proportion of blacks or Hispanics is increased and (ii) how much the extra repositioning caused this type of demand shock would cost. The exercise also provides an additional "reality" check on the model by showing that the available formats do respond in plausible ways to demand shocks.

I do this by drawing using a set of shocks to the growth process of blacks or Hispanics in six representative markets. The markets differ in size and also vary in how large the ethnic population

[30] I calculate these numbers by using the conditional choice probabilities to calculate the expected value of ε conditional on switching.

is in Fall 2005 (the starting point for the simulations). The shocks consist of drawing v^D_{emt}s from the 90^{th} percentile of the distribution of v^D_{emt} for 20 periods (10 years) and then applying the estimated policy functions to see how the set of available formats changes over time.[31]

[TO BE COMPLETED]

7 Conclusion

The medium and long-run effects of demand, supply and policy shocks in differentiated product markets depend heavily on how costly it is for firms to change the set of products they offer. However, the literature has focused on the estimation of demand elasticities, rather than trying to model the drivers or feasibility of supply-side substitution. This paper attempts to fill this gap in the literature by providing estimates of repositioning (format switching) costs in the broadcast radio industry and examining how quickly format positioning changes in response to demand shocks caused by changes in market demographics.

I estimate that it costs a station less than one year's advertising revenues to change its format. The absolute level of costs is much larger in larger markets, suggesting that format switching is costly largely because stations have to spend time and resources developing new relationships with listeners and advertisers, while costs which are the same across markets, such as those associated with replacing a station's music library, appear to be quite small. As a result of repositioning costs being relatively small, the set of available products responds quite quickly to demand shocks.

One of the principal motivations for studying repositioning costs is that they can play an important role in the analysis of mergers. In particular, there may be less reason to be concerned about mergers between firms owning close demand-side substitutes if price increases can be deterred by the threat that other firms would move their products. While considering a full-blown merger application is

[31] This approach implies that, in each period, stations are "surprised" when the growth rate of the particular ethnic/racial group increases. An alternative approach would be to change stations' expectations about future growth, but modelling these effects would require resolving the model which is not feasible given its complexity. This is also the reason why I focus on the effect of demand shocks rather than on a policy change or a change in repositioning costs which could only be examined by solving the model.

beyond the scope of the current paper, the results do have two suggestive implications for merger policy in the radio industry. First, the revenue estimates suggest that commonly owned stations have been able to exercise very little market power over advertisers even though formats do appeal to listeners with radically different demographics. This could be explained either by advertising prices being set in a wider advertising market (e.g., in competition with television stations and newspapers) or because of the possibility that supply-side substitution is operating to constrain market power. Second, because supply-side substitution costs increase with market size, it would be incorrect for a merger analysis to assume that supply-side substitution is necessarily easier, which would suggest having a more relaxed merger policy, in larger markets.

References

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

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

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

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

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

[6] Bayer, Christian and Falko Juessen (2006), "On the Dynamics of Interstate Migration: Migration Costs and Self-Selection", mimeo, University of Dortmund

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

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

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

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

[11] Berry, Steven T., James Levinsohn and Ariel Pakes (1993), "Applications and Limitations of Some Recent Advances in Empirical Industrial Organization: Price Indexes and the Analysis of Environmental Change", *American Economic Review*, 83(2), 240-246

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

[33] Fisher, Franklin M., John F. McGowan and David S. Evans (1980), "The Audience-Revenue Relationship for Local Television Stations", *Bell Journal of Economics*, 11(2), 694-708

[34] Froeb, Luke, Amit Gandhi, Steven Tschantz and Gregory J. Werden (2007), "Post-Merger Product Repositioning", *Journal of Industrial Economics*, forthcoming

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

[36] Gemici, Ahu (2007), "Family Migration and Labor Market Outcomes", mimeo, University of Pennsylvania

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

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

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

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

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

[42] Kennan, John and James R. Walker (2006), "The Effect of Expected Income on Individual Migration Decisions", mimeo, University of Wisconsin-Madison

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

[44] Judd, Kenneth (1985), “Credible Spatial Preemption”, 16(1), *RAND Journal of Economics*

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

[62] Shapiro, Carl, "Mergers with Differentiated Products", speech delivered in Washington, DC, November 9, 1995

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

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

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

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

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

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

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

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

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

Table 1: Formats and Demographics

Formats	Average Format Demographics				
	% Female	% Under 25	% Under 49	% Black	% Hispanic
Adult Contemporary	63.7%	13.9%	70.6%	7%	12%
Contemporary Hit Radio/Top 40	61.0%	47.1%	92.7%	21%	24%
Country	53.2%	15.7%	61.3%	2%	6%
Oldies	51.4%	8.2%	45.8%	6%	15%
Rock	32.3%	23.1%	84.2%	3%	10%
Urban	54.6%	33.3%	80.0%	81%	6%
News/Talk	34.6%	3.3%	44.0%	8%	6%
Other Music	54.4%	7.9%	44.6%	20%	7%
Religion	65.5%	7.8%	57.6%	34%	9%
Spanish Language	48.4%	25.3%	81.1%	1%	96%

Notes: Female and age data calculated based on station-level Arbitron data for Spring 2006. Black, hispanic data based on Arbitron estimates for Spring 2004 reported in 2005 Radio Today report.

Table 2: Format Switching Patterns

FM Stations

From	**Number of station-qtr observations**	**Proport. switching out**	**Proportion of stations switching out, switching to** Dark	AC	CHR	Cntry	Old	Rock	Urban	News	OtherM	Relig	Span
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-language	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

	Number of station-qtr observations	**Proport. switching out**	**Proportion of stations switching out, switching to** Dark	AC	CHR	Cntry	Old	Rock	Urban	News	OtherM	Relig	Span
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-language	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: 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 category to create the instrument. This instrument implicitly assumes that an out of market station's choice of format does not depend on the number of home market stations in a format. This 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 4: Listener Demand Model

	Demographic Effects and Random Coefficients						
	Std Dev of RC	**Age 25-49**	**Age 50 plus**	**Female**	**Black**	**Hispanic**	**AM x Band**
Adult Contemporary	2.127	0.684	0.133	0.638	-0.628	-0.654	-0.385
	(0.487)	(0.085)	(0.113)	(0.073)	(0.074)	(0.093)	(0.182)
CHR/Top 40	2.461	-0.893	-2.740	0.542	0.783	0.153	-0.547
	(0.591)	(0.123)	(0.252)	(0.077)	(0.113)	(0.103)	(0.280)
Country	0.000	0.390	0.412	0.065	-1.896	-1.613	-0.825
	(4.765)	(0.047)	(0.065)	(0.030)	(0.052)	(0.087)	(0.143)
Oldies	-0.003	0.815	1.430	-0.104	-0.809	-0.551	-0.943
	(2.311)	(0.128)	(0.143)	(0.041)	(0.088)	(0.135)	(0.169)
Rock	0.000	0.404	-0.714	-0.726	-1.828	-1.046	-1.175
	(1.308)	(0.045)	(0.070)	(0.031)	(0.045)	(0.064)	(0.185)
Urban	0.290	-0.142	-0.439	0.041	3.624	0.386	-1.106
	(2.180)	(0.084)	(0.131)	(0.035)	(0.176)	(0.089)	(0.154)
News	0.875	8.359	8.968	-0.716	-0.543	-1.413	-0.601
	(0.746)	(152.748)	(152.749)	(0.043)	(0.061)	(0.078)	(0.136)
Other Music	0.000	8.624	9.598	0.010	0.395	-0.976	-0.825
	(1.383)	(556.136)	(556.153)	(0.041)	(0.064)	(0.099)	(0.135)
Religious	0.000	3.085	3.664	0.444	1.560	-0.618	-0.908
	(0.900)	(1.560)	(1.571)	(0.052)	(0.070)	(0.113)	(0.142)
Spanish	-0.084	0.285	0.361	-0.023	-0.476	4.215	-1.256
	(1.013)	(0.070)	(0.117)	(0.048)	(0.049)	(0.055)	(0.146)
Constant (commercial radio)	0.355	-	-	-	-	-	-
	(0.243)						

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Station Quality Parameters	
Signal coverage	1.054
	(0.127)
FM*signal coverage	0.331
	(0.137)
Unlisted station	-1.032
	(0.061)
Out of market station	-0.628
	(0.110)
Signal power FM	4.545
	(7.623)
Signal power AM	1301.403
	(203.379)
Transmitter height FM	11.495
	(44.877)
Station Age	-5.423
	(46.952)
Evolution of Station Quality	
ρ_1^{ξ}	0.872
	(0.004)
Standard deviation of	0.502
innovation non-switchers	(0.002)
ρ_2^{ξ}	0.710
	(0.008)
Standard deviation of	0.613
innovation switchers	(0.018)
Mean change switchers	-0.050
	(0.070)
Observations	42,858
GMM Objective	1782.3
	DoF:758

Table 5: Revenue Function: Alternative Specifications

	(1)	(2)	(3)	(4)
Demographics				
Female	0.1349	0.1518	0.1363	0.1078
	(0.0182)	(0.0192)	(0.0187)	(0.0193)
Age 12-24	-0.5079	-0.4989	-0.565	-0.5913
	(0.0309)	(0.032)	(0.0308)	(0.0309)
Age 50+	-0.4695	-0.4664	-0.4711	-0.4851
	(0.0196)	(0.0201)	(0.0195)	(0.0203)
Black	-0.2283	-0.234	-0.2165	-0.2136
	(0.0117)	(0.0123)	(0.0118)	(0.0115)
Hispanic	-0.1492	-0.1567	-0.126	-0.119
	(0.0106)	(0.0119)	(0.0120)	(0.0118)
Station/Competition				
Number of stations commonly owned in format	-	0.0192	0.0154	0.016
		(0.0038)	(0.0038)	(0.0039)
Number of stations owned by other firms in format	-	-0.0027	-0.002	-0.0009
		(0.0017)	(0.0017)	(0.0017)
Format switch in previous two quarters	-	-0.1422	-0.1232	-0.1211
		(0.0116)	(0.0118)	(0.0119)
Non-linear revenue effects				
Station market share relative to market average	-	-	7.7624	7.446
			(0.6302)	(0.6315)
Proportion of station's audience in demographic group	-	-	-	-0.223
				(0.0374)
Observations (station-year)	13007	13007	13007	13007
R^2	0.258	0.267	0.276	0.278
Measures of Fit				
Change in Revenue for Non-Switchers ($k)				
actual mean (std dev)	188 (1048)	188 (1048)	188 (1048)	188 (1048)
predicted mean (std dev)	120 (1083)	138 (1101)	137 (1154)	137 (1155)
correlation of actual, predicted	0.40	0.40	0.39	0.40
Change in Revenue for Switchers ($k)				
actual mean, std	140 (998)	140 (998)	140 (998)	140 (998)
predicted mean, std	331 (1728)	55 (1507)	102 (1556)	103 (1548)
correlation of actual predicted	0.56	0.52	0.54	0.54

Table 8: Multinomial Logit Model for Conditional Choice Probabilities

	Demographics and Mkt-Format Attractiveness				
	Prop Hispanic	Δ Prop Hispanic	Prop Black	Δ Prop Black	Estimated Mkt-Format Quality
Dark	-	-	-	-	-
AC	-1.233	-13.399	-0.295	-123.065	0.139
	(0.835)	(21.749)	(1.000)	(48.123)*	(0.207)
CHR	-0.758	16.650	0.348	-85.002	0.109
	(0.875)	(22.376)	(1.109)	(50.965)	(0.180)
Country	-0.683	9.040	0.024	-39.996	-0.062
	(0.842)	(22.638)	(1.078)	(50.871)	(0.182)
Oldies	-0.783	-11.693	0.304	-116.572	0.179
	(0.908)	(23.781)	(1.107)	(52.458)*	(0.179)
Rock	-1.143	1.913	-2.138	-53.679	0.262
	(0.813)	(21.606)	(1.055)*	(48.487)	(0.216)
Urban	0.518	13.832	9.949	-93.347	0.468
	(0.938)	(24.753)	(1.691)**	(50.222)	(0.674)
News	-0.660	4.520	0.345	-77.202	0.333
	(0.833)	(21.944)	(1.066)	(49.947)	(0.189)
Other M	-1.471	15.109	0.535	-93.762	-0.005
	(0.864)	(22.186)	(1.052)	(49.315)	(0.104)
Religion	-0.802	-41.027	3.305	-25.938	0.328
	(0.992)	(27.055)	(1.398)*	(55.808)	(0.243)
Spanish	4.457	92.235	1.985	-77.003	0.498
	(1.315)**	(23.776)**	(1.390)	(57.492)	(0.156)**

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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	-0.142	-3.221	-0.079	-0.028
	(0.062)*	(13.694)	(0.067)	(0.064)
CHR	-0.290	24.220	-0.041	-0.002
	(0.094)**	(18.579)	(0.152)	(0.092)
Country	-0.206	24.319	-0.102	-0.026
	(0.070)**	(10.220)*	(0.038)	(0.049)
Oldies	-0.026	-48.132	-0.044	0.002
	(0.142)	(32.585)	0.054	(0.108)
Rock	-0.066	-11.691	-0.058	0.071
	(0.049)	(13.883)	(0.022)	(0.053)
Urban	0.083	-51.279	-0.041	0.188
	(0.067)	(15.004)**	(0.037)	(0.060)**
News	-0.093	-6.725	-0.047	0.043
	(0.057)	(16.109)	(0.096)	(0.045)
Other M	-0.038	9.785	-0.067	-0.040
	(0.073)	(16.442)	(0.056)	(0.055)
Religion	0.041	-100.485	-0.050	0.098
	(0.086)	(33.732)**	(0.028)	(0.056)
Spanish	0.140	-71.534	-0.061	0.158
	(0.069)*	(24.498)**	(0.002)	(0.046)**

Biggest station in format x stay	0.419	Current share x switch to dark	-926.207
	(0.096)**		(262.634)**
Current share x switch	-163.589		
	(13.744)**		

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Switch Variables

	Stay x FM	Stay x AM	Switch x FM	Switch x AM
Dark	4.400	3.842	-	-
	(0.489)**	(0.409)**		
AC	6.847	6.313	3.237	0.244
	(1.706)**	(1.706)**	(1.698)	(1.706)
CHR	5.268	4.217	1.693	-1.500
	(1.135)**	(1.218)**	(1.131)	(1.175)
Country	4.860	4.199	0.141	-0.641
	(1.315)**	(1.281)**	(1.303)	(1.272)
Oldies	6.341	6.134	2.236	1.092
	(1.417)**	(1.388)**	(1.408)	(1.393)
Rock	7.578	5.329	3.565	0.687
	(1.393)**	(1.383)**	(1.381)**	(1.384)
Urban	7.000	7.002	2.983	1.380
	(0.959)**	(0.929)**	(0.950)**	(0.929)
News	9.985	10.126	4.297	6.124
	(2.616)**	(2.600)**	(2.602)	(2.586)*
Other M	4.396	4.135	0.063	0.475
	(1.021)**	(0.965)**	(1.017)	(0.971)
Religion	9.150	9.048	3.176	3.415
	(1.346)**	(1.303)**	(1.337)*	(1.302)**
Spanish	8.492	8.016	2.938	2.789
	(0.883)**	(0.816)**	(0.851)**	(0.787)**

Switch x Mkt Pop

200k-500k	500k-1m	1m-2m	2m-4m	4m+
0.011	0.009	-0.243	-0.365	-0.443
(0.085)	(0.0932)	(0.096)*	(0.108)**	(0.153)**

continues over....

Ownership Variables & Miscellaneous Variables

	Number stations commonly owned nationwide
Dark	-
AC	0.005
	(0.002)**
CHR	0.012
	(0.002)**
Country	0.008
	(0.002)**
Oldies	0.010
	(0.004)*
Rock	0.005
	(0.002)**
Urban	0.015
	(0.005)**
News	0.009
	(0.001)**
Other M	0.009
	(0.006)
Religion	0.034
	(0.011)**
Spanish	0.046
	(0.008)**

Recent ownership switch	0.409
	(0.069)**
Number owned in current market-format x stay	-0.07
	(0.045)
Number owned in alternative market format x switch	0.118
	(0.047)*
Stations commonly owned by other firms in current format	0.023
	(0.062)
Stations commonly owned by other firms in alternative format	0.051
	(0.057)
Recent Format Switch	0.058
	(0.077)

Table 7: Bounds on Switching Costs

	Range $m	95% CI	UB E(S+ε) given switch
All markets	[0.43,4.88]	[0.24,7.83]	2.03
Large markets (Chicago - Minneapolis)	[1.54,15.51]	[1.02,25.67]	6.94
Medium markets (St Louis - Albuquerque, NM)	[0,2.42]	[0,4.56]	1.32
Small markets (Spokane - Bismarck, ND)	[0.023,1.595]	[0,2.55]	0.57

Figure 1: Market Shares of Switching Stations

(share in quarter prior to switch normalized to zero)

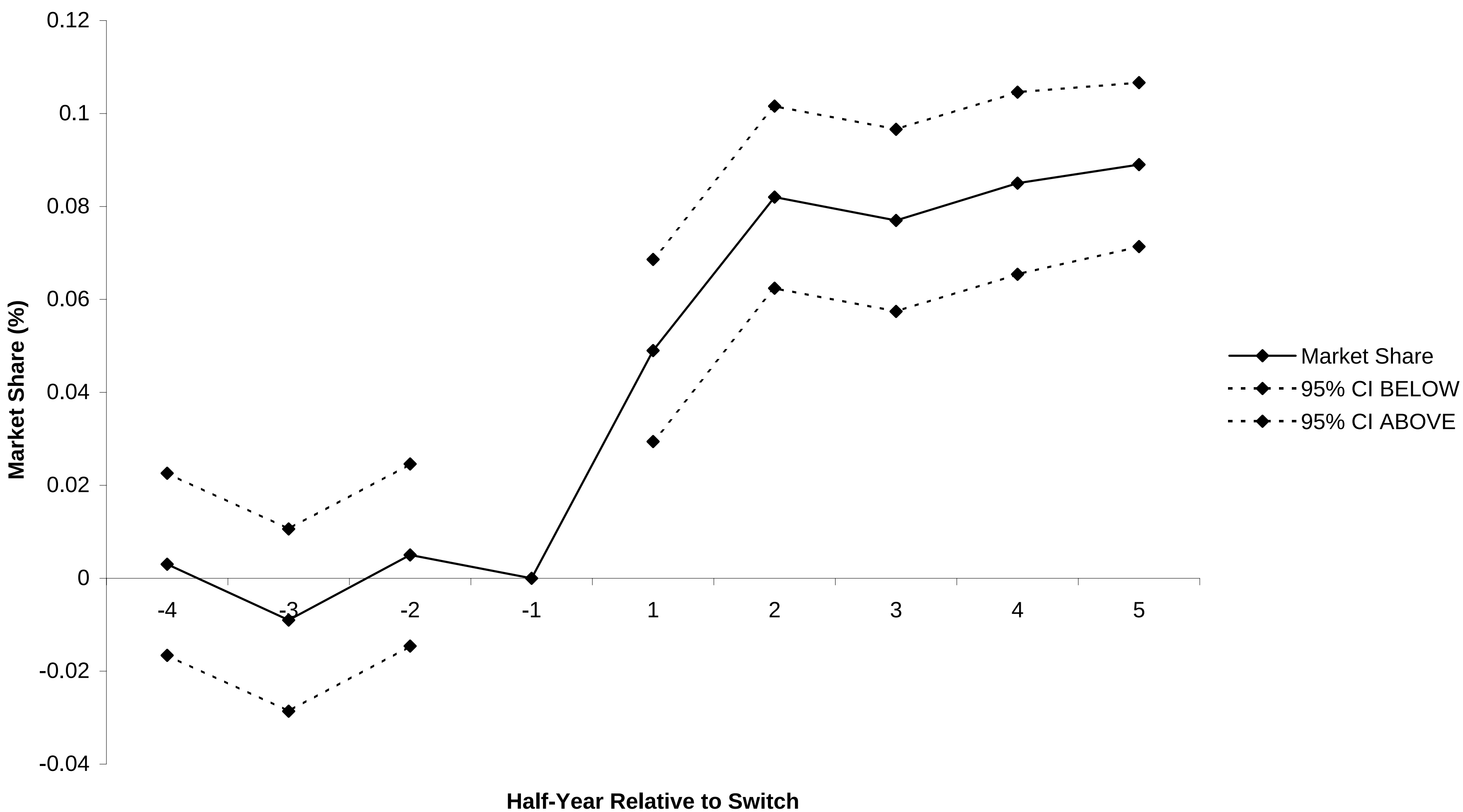

Figure 2: Distribution of Share Changes and Its Relationship With Format Switching

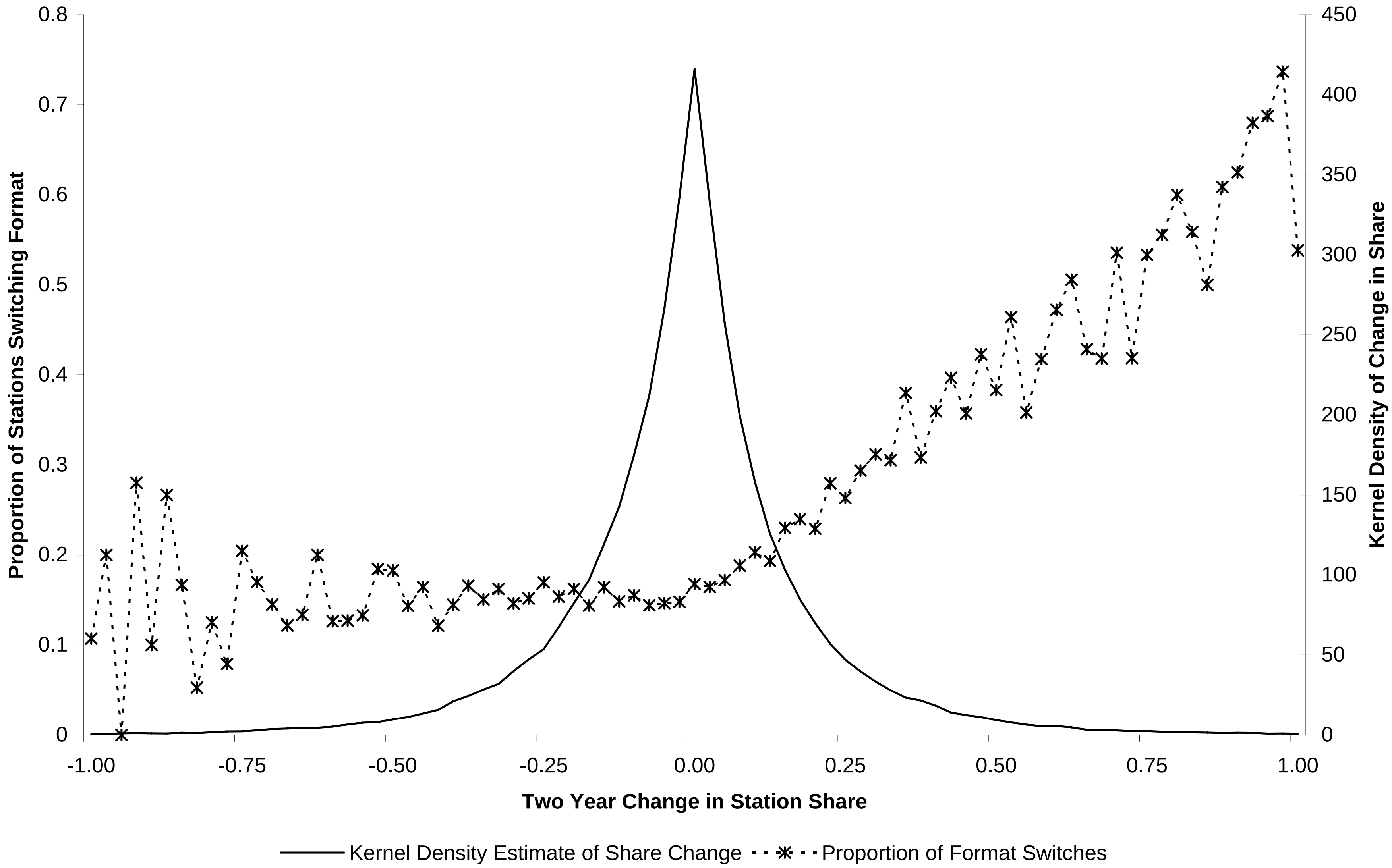

Figure 3: Relationship Between Switching Rate and Average Number of Listeners Per Station

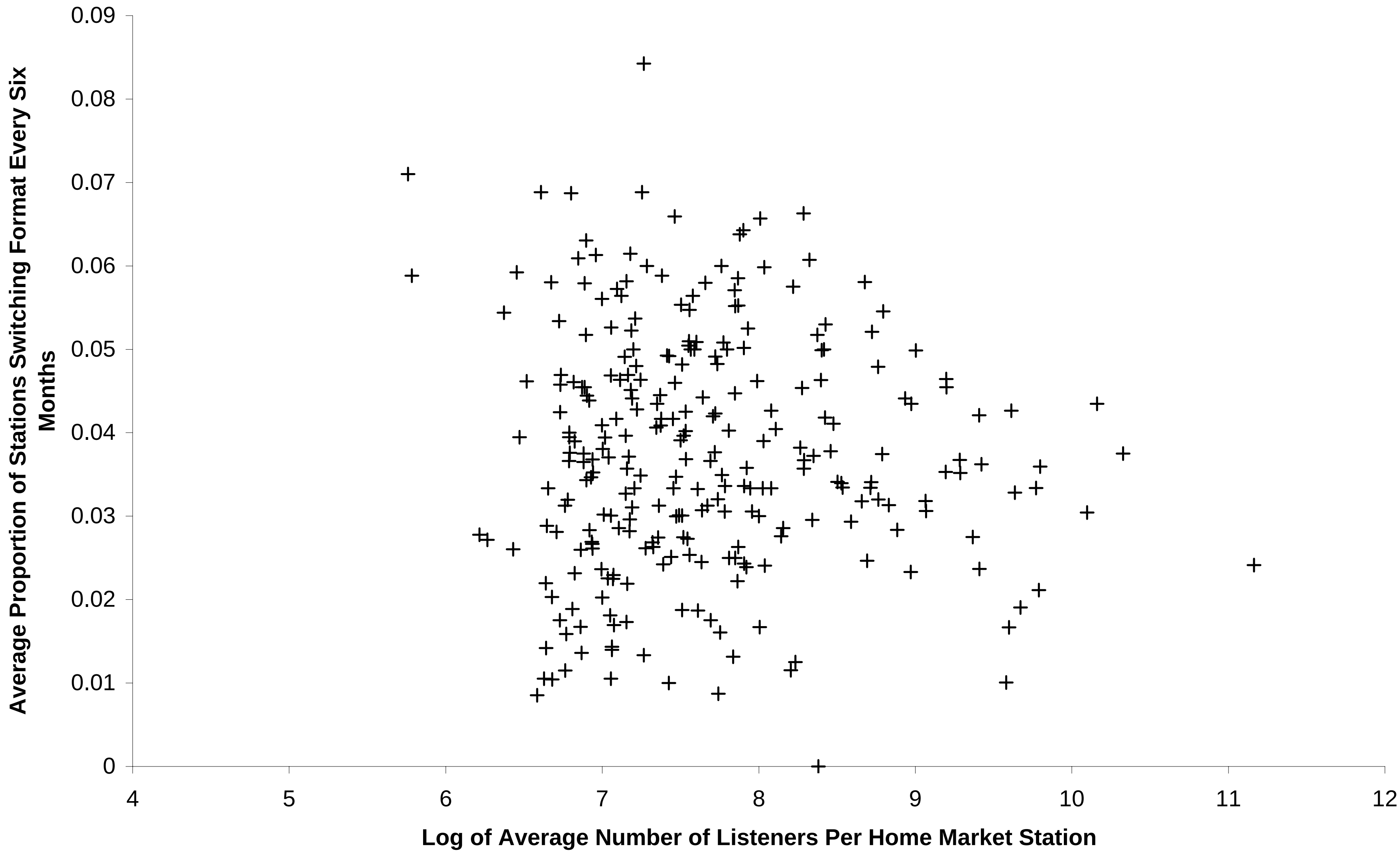

Figure 4: Market Shares of Switching Stations By Market Size
(share in quarter proceeding switch normalized to zero)

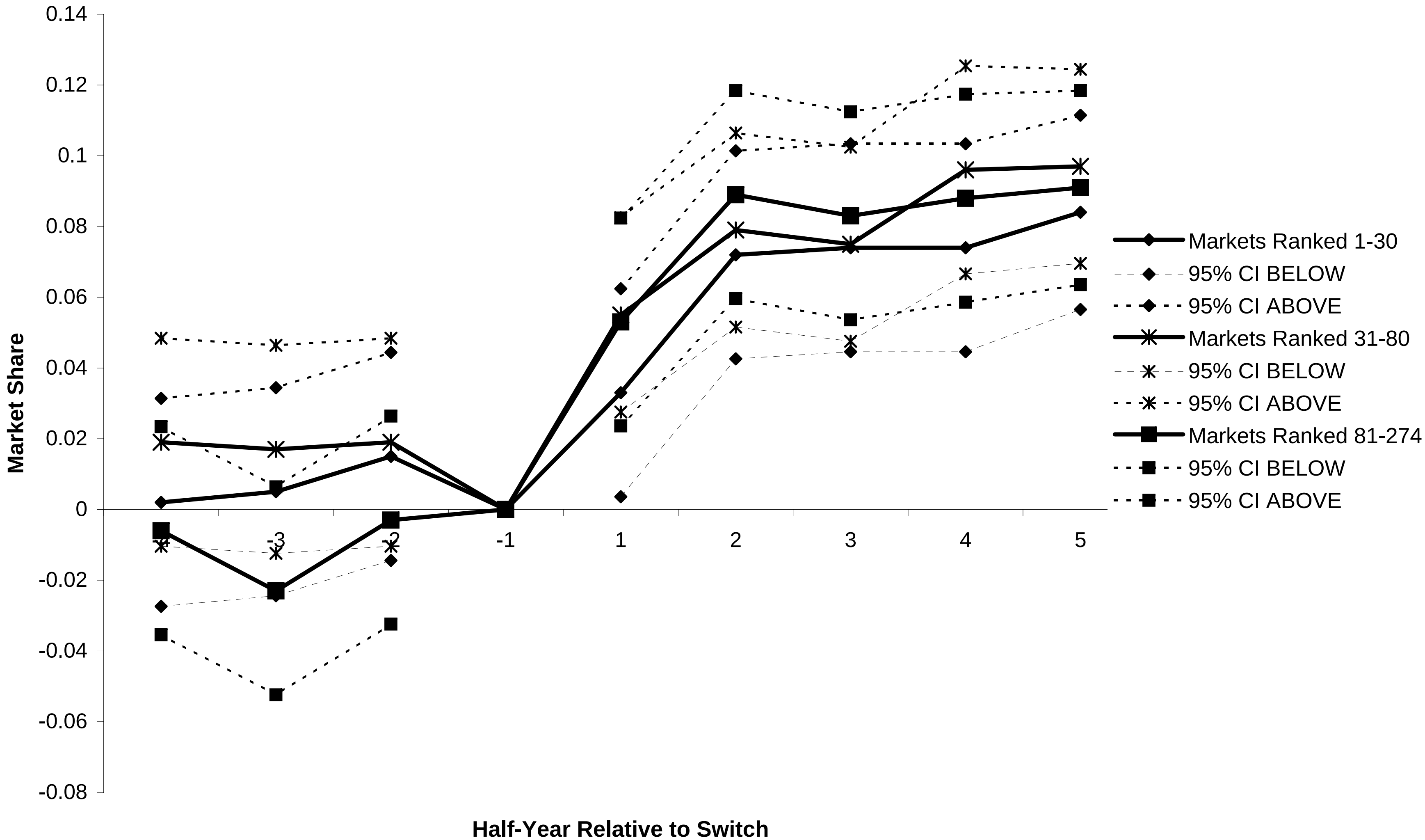

Figure 5: Inequalities: All Markets

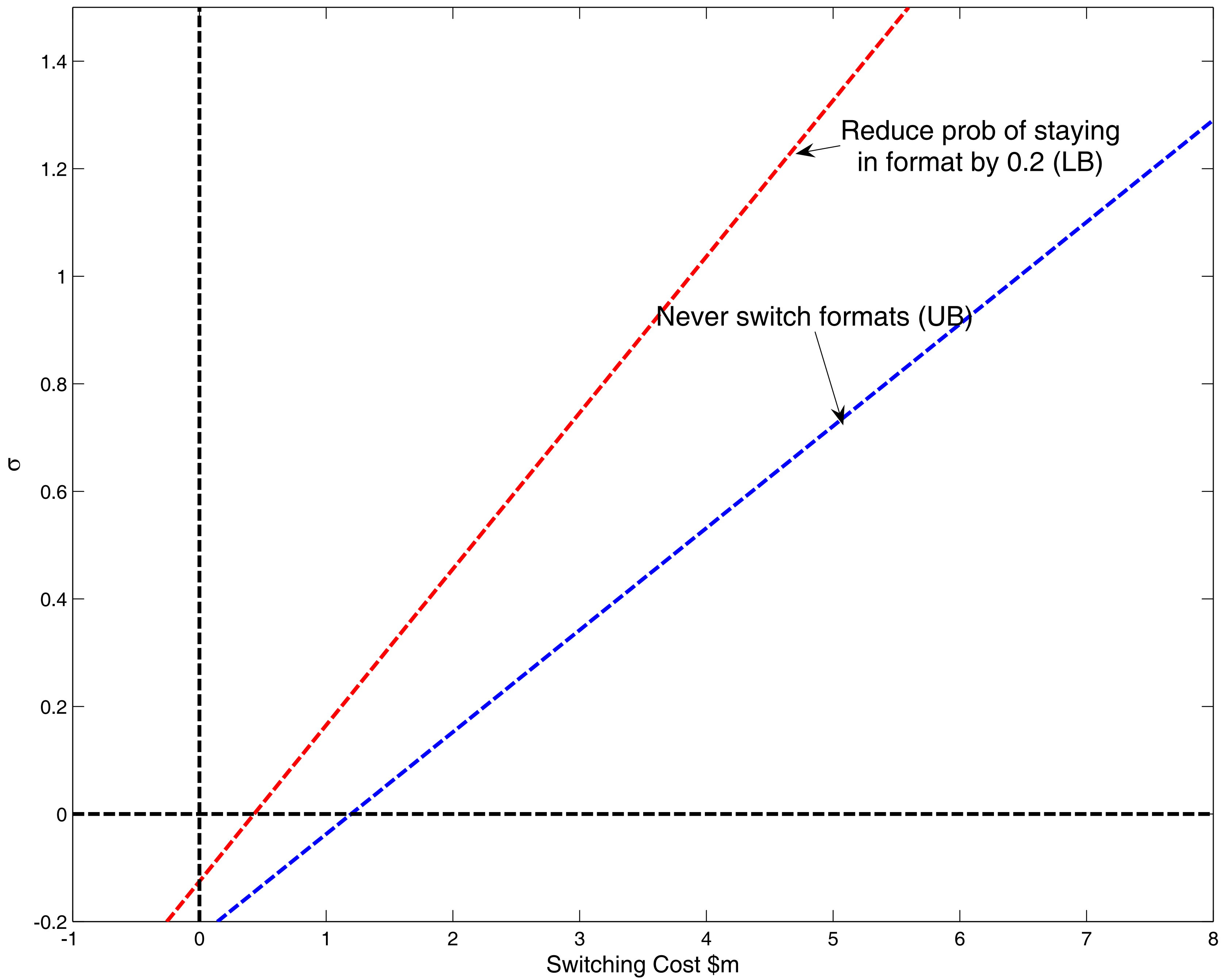

Figure 6: Inequalities: All Markets

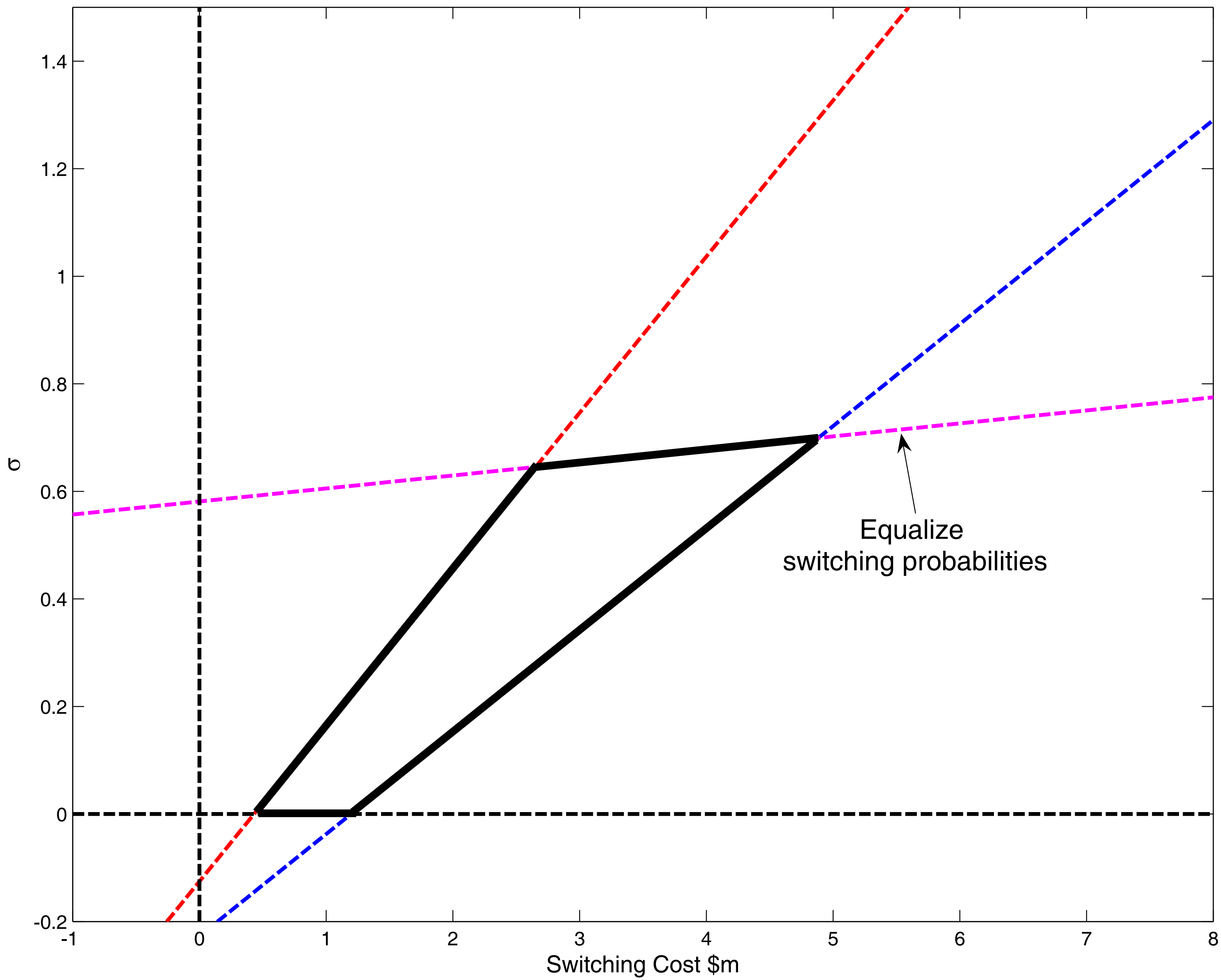

Figure 7: Innovations in Station Quality

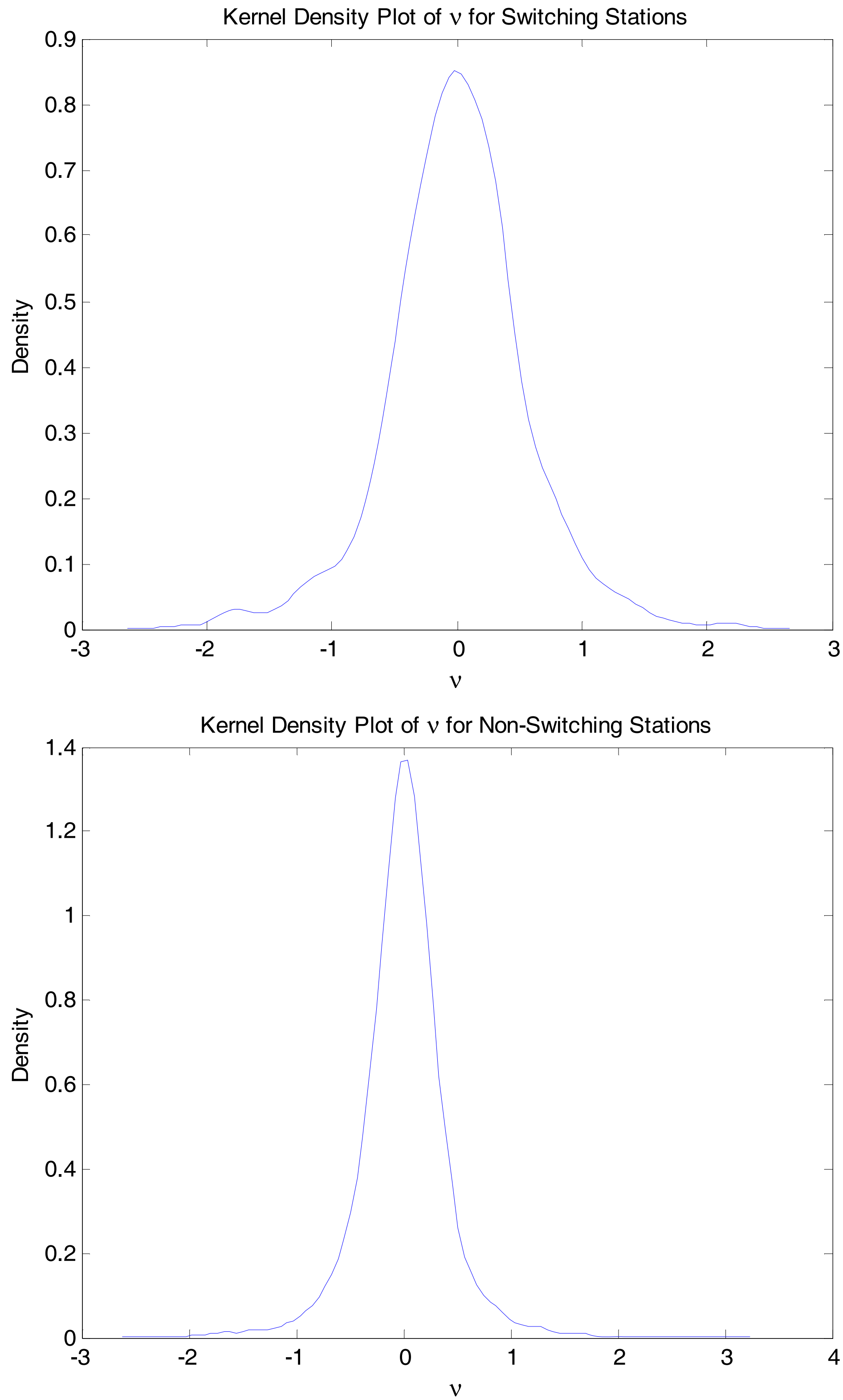

Figure 7 cont.: Empirical Distribution of Unobserved Station Qualities

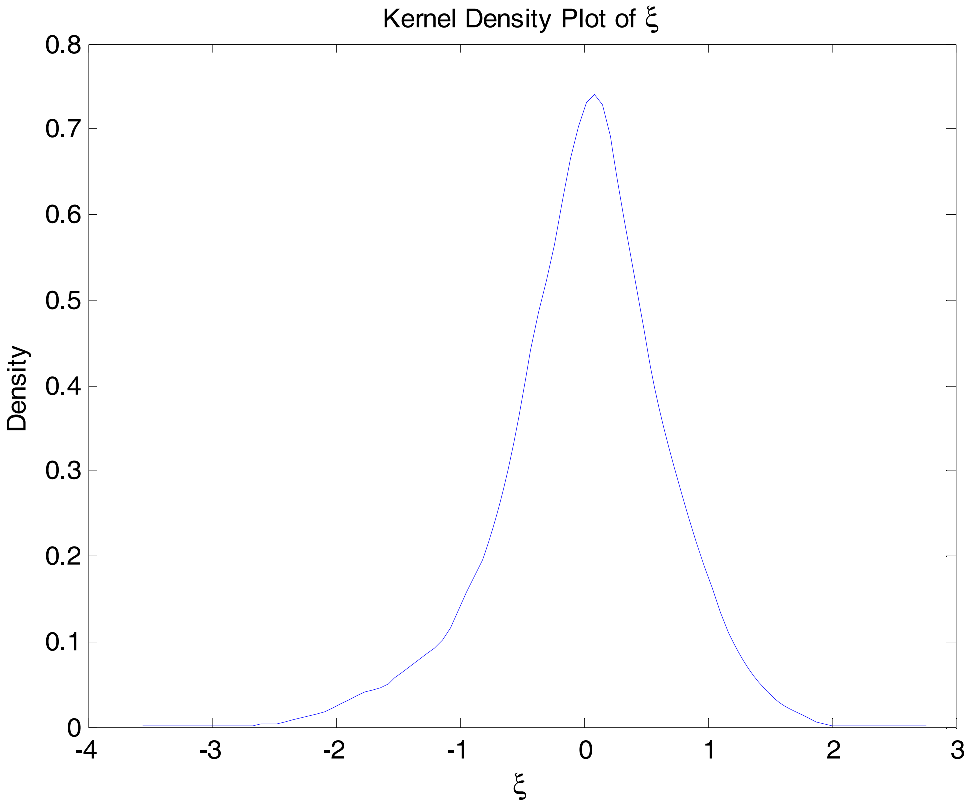

Figure 8: Simulated vs. Actual Changes in Share for Switching and Non-Switching Stations