ESSAYS ON HORIZONTAL MERGERS AND ANTITRUST

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Abstract

This thesis contributes to understanding the economics of mergers and acquisitions. It provides new empirical techniques to study these processes, based on structural, game theoretical models. In particular, it makes two main contributions. In Chapter 2, I study the issues arising when mergers take place in a two-sided market. In such markets, firms face two interrelated demand curves, which complicates the decision making process and makes standard merger models inapplicable. In Chapter 3, I provide a general framework to identify cost synergies from mergers without using cost data. The estimator is based on a dynamic model with endogenous mergers and product repositioning. Both chapters contain an abstract model that can be tailored to many markets, as well as a specific application to the merger wave in the U.S. radio industry.
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Chapter 1

Introduction

A horizontal merger occurs when two or more competing companies combine to jointly operate. Both the European Commission (2004) and the U.S. Department of Justice (1997) recognize that such mergers may lessen competition and thereby harm consumers. Therefore, in order to prevent anti-competitive conduct, both bodies employ a set of analytical tools that predict and analyze the consequences of mergers. The dominant paradigm from the 1950s and through the 1970s was the structure-conduct-performance approach (see Bain (1968)). It assumes that market power is directly related to market concentration, and proposes using concentration indexes (e.g. the Herfindahl-Hirschman Index) for merger enforcement. This approach however, does not explicitly explain the conduct of firms and ignores many important issues, for example product differentiation, and heterogeneity of consumers or cost synergies. In contrast, modern industrial organization has developed new techniques, based on game theory, that endogenize the behavior of companies and allow for more detailed and robust evaluation of mergers.

Current analysis of horizontal mergers in markets with differentiated products is based on a static supply and demand approach (e.g. Nevo (2000)). It is usually done in two steps. In the first step, one estimates a flexible demand system (e.g. Deaton and Muellbauer (1980), Ackerberg and Rysman (2005), Berry (1994), Berry, Levinsohn, and Pakes (1995)) and supply system. The demand system is a function of product characteristics, prices and heterogeneous consumer preferences. The supply
system is determined by the equilibrium behavior of firms that maximize their profits. In the second step, one exogenously imposes a hypothetical merger and solves for the post-merger equilibrium using the estimates from the first step. The new equilibrium provides predictions about post-merger prices and quantities that can be used to identify the short-run impact of the merger on consumer and producer surplus. This thesis provides two extensions to this framework. First, it develops a new supply and demand system that encompasses the merger analysis of two-sided markets. Second, it proposes a dynamic framework in which mergers and product repositioning are endogenous. It allows for long-run predictions, including evaluation of possible fixed cost synergies of mergers. These methods are applied to analyze the 1996-2006 merger wave in the U.S. radio industry.

In the chapter 2 of this thesis, I focus on how mergers affect two-sided markets. In a two-sided market, firms provide services to two types of consumers and facilitate their interaction via a platform. This creates cross-consumer externalities; thus, the profits of a firm operating a platform depend on sales to both types of consumers. Examples of such markets include the following: radio, in which stations sell ads and provide programming to listeners; credit cards, in which firms connect merchants and credit card holders; operating systems, in which revenue comes from hardware buyers and application developers. Antitrust analysis in these markets is complicated and it must take into account the market specific economic features (Armstrong (2006), Rochet and Tirole (2006), Evans (2002)). In particular, in the case of a merger, a firm has incentives to exercise market power on both sides of the market. These incentives are often conflicting. For example, in the radio market, stations sell advertising knowing it negatively impacts their listenership. On the one hand, a merged firm might sell more advertising in order to exercise market power on listeners. On the other hand, it might sell less advertising in order to exercise market power on advertisers. Chapter 2 investigates this conflict by estimating a model of supply and demand for advertising and radio programming. Using this model, it performs counterfactual experiments that predict the post-merger advertising quantity supplied and the new division of surplus between listeners and advertisers. I find that mergers decrease the amount of advertising supplied, thereby increasing listener welfare by 1%. However, at the same
time the decrease in ad supply raises prices and lowers advertiser welfare by $300m per year.

A static analysis does not recognize that firms may adjust their product portfolio after a merger. In theory, mergers could increase or decrease product variety. On the one hand, they can increase the variety because a merged firm wants to avoid cannibalization. On the other hand, the firm might crowd products together to prevent entry. In the former case, if consumers prefer more variety, it is possible that repositioning could alleviate the negative effects of the merger (Berry and Waldfogel (2001), Sweeting (2008)). Chapter 2 provides a method to disaggregate the total impact of the merger on consumer surplus into changes in product variety and in supplied quantity. The same method can be used to predict whether extra variety could alleviate negative market power effects for a hypothetical merger. In the case of radio, extra variety alone leads to a 1.3% increase in listener welfare and decreases advertiser welfare by $147m per year. I find that product ownership consolidation and repositioning are followed by advertising quantity reallocations. I estimate that this effect alone leads to a 0.3% decrease in listener welfare (with the variety effect it sums to a 1% increase) and an additional $153m decrease in advertiser welfare (with the variety effect it totals $300m). While extra variety mitigates the negative effects of mergers on listeners, it increases the negative impact on advertisers.

Chapter 3 deals with a dynamic merger analysis. The current empirical literature on mergers and repositioning assumes that the market structure is exogenous (Nevo (2000), Pinkse and Slade (2004), Ivaldi and Verboven (2005)). This approach does not take into account dynamic processes like post-merger repositioning, follow-up mergers, and fixed cost synergies, that could potentially lower prices and provide consumers with other non-price benefits. Moreover, the assumption that mergers are exogenous may create a selection bias that results in overestimation of cost synergies (for example the estimator might pick up other unobserved components correlated with the propensity to merge). This thesis provides a new, dynamic framework in which decisions to merge and to reposition products are endogenous. Such an approach provides consistent estimates of the long-run effects of mergers. In addition, it allows for the estimation of cost synergies without any data on cost. The framework
is straightforward, easy to implement, and computationally tractable. Application to radio reveals that the 1996-2006 merger wave provided $2.5b per year of cost synergies, which constitutes about 10% of total industry revenue. The scale of those efficiencies is a an order of magnitude higher than loss in surplus for advertisers.
Chapter 2

Mergers in two-sided markets: Case of U.S. radio industry

2.1 Preface

This chapter studies the consequences of mergers in two-sided markets by estimating a structural supply and demand model and performing counterfactual experiments. The analysis is performed on the example of a merger wave in U.S. radio; however, it is applicable to other two-sided markets like credit cards, trading platforms or computer games. There are two main contributions from this chapter. First, I identify the conflicting incentives of merged firms to exercise market power on both sides of the market (listeners and advertisers in the case of radio). Second, I disaggregate the effect of mergers on consumers into changes in product variety and changes in supplied ad quantity.

The model is estimated using data on 13,000 radio stations from 1996 to 2006. I find that firms have moderate market power over listeners in all markets, extensive market power over advertisers in small markets and no market power over advertisers in large markets. Counterfactuals reveal that extra product variety created by post-merger repositioning increased listeners’ welfare by 1.3% and decreased advertisers’ welfare by about $160m per-year. However, subsequent changes in supplied ad quantity decreased listener welfare by 0.4% (for a total impact of +0.9%) and advertiser welfare by an additional $140m (for a total impact of -$300m).


2.2 Introduction

Between 1996 and 2006, the U.S. radio industry experienced an unprecedented merger wave due to the 1996 Telecommunication Act, which raised ownership caps in local markets and abolished cross-market ownership restrictions. At the height of merger activity, about 30% of stations changed ownership each year and about 20% changed the format of broadcasted programming. In this paper, I use this merger wave to study the consequences of consolidation in two-sided markets. I make two main contributions. First, I identify conflicting incentives for stations to exercise market power on both sides of the market (in the case of radio, the two sides are advertisers and listeners). In particular, I separate the impact of consolidation on listener and advertiser surplus. Second, I decompose this impact into effects of changes on product variety and market power. As a result, I ask whether extra variety can mitigate the negative effects of a decrease in competition. Similar issues arise in other two-sided markets such as credit cards, newspapers or computer hardware. The framework proposed in this paper can be easily adjusted to analyze any of these industries.

In two-sided markets, firms face two interrelated demand curves from two distinct types of consumers. These demands give merging firms conflicting incentives because exercising market power in one market lowers profits in the other market. In the case of radio, a company provides free programming to listeners but draws revenue from selling advertising that is priced on a per-listener basis. In the listener market, a merged firm would like to increase post-merger advertising because it captures some switching listeners. This advertising decreases the welfare of listeners and increases the welfare of advertisers. However, from the perspective of the advertising market, the merged firm would like to supply less advertising, which has the exact opposite impact on listener and advertiser welfare. The firm’s ultimate decision, which determines the impact of consolidation on the welfare of both consumer groups, depends on the relative demand elasticities in both markets.

In this paper, I separately estimate elasticities for both consumer groups using a structural model of the demand and supply of radio programming and advertising. Using those estimates, I perform counterfactual policy experiments that quantify the
impact of consolidation on listener and advertiser surplus. I find that market power on the listener side is similar across geographical markets. In contrast, the amount of market power on the advertiser side depends on market population. In particular, firms have a considerable control over advertising price in smaller markets; however, they are price takers in larger markets. Consequently, mergers result in firms lowering advertising quantity in small markets (less than 500 thousand people) by about 13%, which leads to a 6% per-listener increase in ad prices. Mergers increase listener surplus by 2.5% but at the same time decrease advertiser surplus by $235m per year. Conversely, in large markets (more than 2 million people) mergers lead to a 5.5% increase in total advertising minutes while per-listener price stays constant. This results in a 0.3% decrease in listener welfare as well as a slight decrease in advertiser welfare ($0.1m per year). The aggregate national impact of the merger wave amounted to a listener welfare gain of 1% and a $300m per year advertiser welfare loss. I conclude that listeners benefited and advertisers were disadvantaged by the 1996 Telecom Act.

My work is related to several theoretical papers studying complexity of pricing strategies in two-sided markets. The closest studies related to this paper are: Armstrong (2006), Rochet and Tirole (2006), Evans (2002) and Dukes (2004). The general conclusion in this literature is that using a standard supply and demand framework of single-sided markets might be not sufficient to capture the economics of two-sided markets. Additionally, there have been several empirical studies on this topic. For example Kaiser and Wright (2006), Argentesi and Filistrucchi (2007) and Chandra and Collard-Wexler (2009) develop empirical models that recognize the possibility of market power in both sides of the market. They use a form of the Hotelling model proposed by Armstrong (2006) to deal with product heterogeneity. I build on their work, incorporating recent advances in the literature on demand with differentiated products. This allows me to incorporate richer consumer heterogeneity and substitution patterns (e.g. Berry, Levinsohn, and Pakes (1995), and Nevo (2000)) that are necessary to capture complicated consumer preferences for radio programming. Moreover, I supplement reduced form results on market power with out-of-sample counterfactuals that explicitly predict changes in supplied ad quantity and consumer welfare.
CHAPTER 2. MERGERS IN TWO-SIDED MARKETS

The second contribution of this paper is the decomposition of the total impact of mergers on consumer surplus into changes in product variety and effects of exercising extra market power from joint ownership. This exercise is motivated by the fact that in most cases consumers have preference for variety, so it is possible that extra variety created by mergers might mitigate the negative effects of extra market power. In order to verify the above claim, I quantify consumers’ value for extra variety and compare it to the loss in surplus coming from the extra market power. This approach relates to Kim, Allenby, and Rossi (2002), who compute the compensating variation for the changes of variety in tastes of yogurt and Brynjolfsson, Hu, and Smith (2003) who do the same for the variety of books offered in on-line bookstores. These papers assume away the fact that changes in variety will be followed by readjustments in equilibrium prices. In this paper, taking their analysis one step forward, I incorporate such strategic responses by performing counterfactual experiments.

Berry and Waldfogel (2001) and Sweeting (2008) document that the post-1996 merger wave resulted in an increase in product variety. I investigate their claim using a structural utility model and conclude that extra variety alone leads to a $1.3\%$ increase in listener welfare. However, because product repositioning softened competition in the advertising market and caused some stations to switch to a “Dark“ format \(^1\), advertiser welfare decreased by $147$m per year. Additionally, I find that product ownership consolidation and repositioning are followed by advertising quantity readjustments. I estimate, that effect alone leads to a 0.3\% decrease in listener welfare (with the variety effect it totals to the 1\% increase) and an additional $153$m decrease in advertiser welfare (with the variety effect it totals $300$m). While extra variety mitigates the negative effects of mergers on listeners, it strengthens the negative impact on advertisers.

This paper is organized as follows. Section 2 outlines the questions investigated in the paper in a formal way and describes the structural model of the industry. Section 3 contains the description of the data. Estimation techniques used to identify the parameters of the model are described in Section 4. Results of the structural

\(^1\)When in “dark” format, the station holds the frequency so that other stations cannot use it. “Dark” stations typically do not broadcast or broadcast very little non-commercial programming.
estimation are presented in Section 5. Section 6 describes the results of counterfactual experiments. Robustness checks of different modeling assumptions are contained in Section 7. Section 8 provides the conclusion.

2.3 Radio as a two-sided market

The radio industry is an example of a two-sided market (other examples include advertising platforms, credit cards or video games). Such markets are usually characterized by the existence of three types of agents: two types of consumers and a platform provider. What distinguishes this setup from a standard differentiated product oligopoly is that the platform provider is unable to set prices for each type of consumer separately. Instead, the demand curves are interrelated through a feedback loop in such a way that quantity sold to one consumer determines the market clearing price for the other consumer. In this subsection I argue that this feedback makes it complicated to determine whether the supplied quantities are strategic substitutes or complements (as defined in Bulow, Geanakoplos, and Klemperer (1985)). This creates important trade-offs in the case of a merger and affects the division of surplus between both types of consumers. The remainder of this subsection discusses this mechanism in detail using the example of radio; however, the discussion applies to the majority of other two-sided markets.

In the case of radio there are three types of agents: radio stations, listeners, and advertisers. Radio stations provide free programming for listeners and draw revenue from selling advertising slots. First, consider the demand curve for radio programming. The listener market share of the radio station \( j \) is given by

\[
  r_j = r_j(q|s,d,θ^L) \quad (2.1)
\]

where \( q \) is the vector of advertising quantities, \( s \) are observable and unobservable characteristics of all active stations, \( d \) are market covariates and \( θ^L \) are parameters of the listener demand. Since radio programming is free, there is no explicit price in this equation. However, because listeners have disutility for advertising, its effect is
similar to price, i.e. $\frac{\partial r_j}{\partial q_j} < 0$.

The market clearing price of an advertising slot in station $j$ depends on the amount of advertising supplied and the number of listeners to station $j$. Therefore, the inverse demand curve for advertising slots is

$$p_j = p_j(q, r_j(q)|s, d, \theta^A) \quad (2.2)$$

where $\theta^A$ are parameters. Note that the advertising quantity affects the advertising price in two ways: directly through the first argument and indirectly through the listener demand feedback loop (the second argument).

Suppose for now that each owner owns a single station and there is no marginal cost (I relax these assumptions later). In equilibrium, each radio station chooses their optimal ad quantity, keeping the quantities of the other stations fixed, i.e.

$$\max_{q_j} p_j(q, r_j(q)|q_{-j})q_j \quad (2.3)$$

In contrast to a differentiated products oligopoly, the firm has just one control (ad quantity) that determines the equilibrium point on both demand curves simultaneously. The first order conditions for profit maximization are given by

$$\frac{\partial p_j}{\partial q_j}q_j + \frac{\partial p_j}{\partial r_j} \frac{\partial r_j}{\partial q_j}q_j + p_j = 0$$

The important fact is that this condition shares features with both the Cournot and Bertrand models. On the one hand, the first term represents the direct effect of quantity on price, and it is reminiscent of the standard quantity setting equilibrium (Cournot). On the other hand, the second component represents the listener feedback loop and is reminiscent of the price setting model (Bertrand), because ad quantities function like prices in the demand for programming.

In order to determine the impact of a merger on the equilibrium ad quantities supplied we need to know if they are strategic complements or substitutes. The duality described in the previous paragraph make it ambiguous. This is because in the Cournot model quantities are strategic substitutes and in the differentiated
product Bertrand model prices are strategic complements. Without knowing the
relative strengths of the direct effects and the feedback loop, we cannot conclude
whether a merger leads to an increase or decrease in ad quantity on the margin.
Moreover, in the borderline case in which the effects cancel each other, a merger does
not effect quantity at all; in this case, even though companies have market power
over both consumers, they are unable to exercise it. Measuring these effects is critical
for predicting the split of surplus between advertisers and listeners. When the direct
effect is stronger, mergers lead to contraction in the ad quantity supplied and higher
prices. This will benefit listeners but hurt advertisers. However, if the feedback loop
is stronger than the direct effect then merger leads to more advertising and lower
prices, benefiting advertisers and hurting listeners.

Because the theory does not give a clear prediction about the split of surplus, I
investigate this question empirically using a structural model. In the remainder of
this section I put more structure on equations (2.1), (2.2) and (2.3), enabling separate
identification of both sets of demand elasticities. I discover the relative strength of
the direct and feedback effects and perform counterfactuals that quantify the extent
of surplus reallocation.

2.3.1 Industry setup

During each period $t$, the industry consists of $M$ geographical markets that are char-
acterized by a set of demographic covariates $d \in D_m$. Each market $m$ can have up to
$J^m$ active radio stations and $K^m$ active owners. Each radio station is characterized by
one of $F$ possible programming formats. Station formats include the so-called “dark”
format when a station is not operational The set of all station/format configurations
is given by $F^{J^m}$. Ownership structure is defined as a $K^m$-element partition of sta-
tion/format configuration $s^{mt} \in F^{J^m}$. In an abuse of notation, I will consider $s^{mt}$
to be a station/format configuration for market $m$ at time $t$, as well as an owner-
ship partition. Each member of the ownership partition (denoted as $s_k$) specifies the
portfolio of stations owned by firm $k$. 
The quality of the programming of radio station \( j \) is fully characterized by a one-dimensional quality measure \( \xi_j \in \Xi \subset \mathbb{R} \). The state of the industry at time \( t \) in market \( m \) is therefore fully characterized by: a station/format configuration and ownership structure \( s^{tm} \), vector of station quality measures \( \xi^{tm} \) and market covariates \( d^{tm} \). In the next subsections I present a detailed model of listener demand, advertiser demand, and supply side. Throughout the description I take the triple \((s^{tm}, \xi^{tm}, d^{tm})\) as given and frequently omit market or time subscripts to simplify the notation.

### 2.3.2 Listeners

This subsection describes the details of the demand for listenership introduced in equation (2.1). The model will be a variation on the random coefficient discrete choice setup proposed by Berry, Levinsohn, and Pakes (1995).

I assume that each listener chooses only one radio station to listen to at a particular moment. Suppose that \( s \) is a set of active stations in the current market at a particular time. For any radio station \( j \in s \), I define a vector \( \iota_j = (0, \ldots, 1, \ldots, 0) \) where 1 is placed in a position that indicates the format of station \( j \).

The utility of listener \( i \) listening to station \( j \in s \) is given by

\[
u_{ij} = \theta^L_{1i} \iota_j - \theta^L_{2i} q_j + \theta^L_{3i} \text{FM}_j + \xi_j + \epsilon_{ji}
\]  

where \( \theta^L_{2i} \) is the individual listener’s demand sensitivity to advertising, \( q_j \) the amount of advertising, \( \xi_j \) the unobserved station quality, \( \epsilon_{ji} \) an unobserved preference shock (distributed type-1 extreme value), and finally \( \theta^L_{1i} \) is a vector of the individual listener’s random effects representing preferences for formats.

I assume that the random coefficients can be decomposed as

\[
\theta^L_{1i} = \theta^L_1 + \Pi D_i + \nu_{1i}, \quad D_i \sim F_m(D_i|d), \quad \nu_{1i} \sim N(0, \Sigma_1)
\]

and

\[
\theta^L_{2i} = \theta^L_2 + \nu_{2i}, \quad \nu_{2i} \sim N(0, \Sigma_2)
\]

where \( \Sigma_1 \) is a diagonal matrix, \( F_m(D_i|d) \) is an empirical distribution of demographic
characteristics, \( \nu_i \) is unobserved taste shock, and \( \Pi \) is the matrix representing the correlation between demographic characteristics and format preferences. I assume that draws for \( \nu_i \) are uncorrelated across time and markets.

The random effects model allows for fairly flexible substitution patterns. For example, if a particular rock station increases its level of advertising, the model allows for consumers to switch proportionally to other rock stations depending on demographics.

Following Berry, Levinsohn, and Pakes (1995), I can decompose the utility into a part that does not vary with consumer characteristics

\[
\delta_j = \delta(q_j|\iota_j, \xi_j, \theta^L) = \theta_1^L \nu_i - \theta_2^L q_j + \theta_3^L FM_j + \xi_j
\]

an interaction part

\[
\mu_{ji} = \mu(\iota_j, q_j, \Pi D_i, \nu_i) = (\Pi D_i + \nu_1 i) \iota_j + \nu_2 q_j
\]

and error term \( \epsilon_{ji} \).

Given this specification, and the fact that \( \epsilon_{ji} \) is distributed as an extreme value, one can derive the expected station rating conditional on a vector of advertising levels \( q \), market structure \( s \), a vector of unobserved station characteristics \( \xi \), and market demographic characteristics \( d \),

\[
r_j(q|s, \xi, d, \theta^L) = \int \int \frac{\exp[\delta_j + \mu_{ji}]}{\sum_{j' \in s} \exp[\delta_{j'} + \mu_{j'i}]} dF(\nu_i)dF_m(D_i|d)
\]

### 2.3.3 Advertisers

In this subsection I present the details of the demand for advertising introduced in equation (2.2). The model captures several important features specific to the radio industry. In particular, the pricing is done on a per-listener basis, so that the price for a 60sec slot of advertising is a product of cost-per-point (CPP) and station rating (market share in percents). Moreover, radio stations have a direct market power over advertisers, so that CPP is a decreasing function of the ad quantities offered by a
station and its competitors. The simplest model that captures these features and is a good approximation of the industry is a linear inverse demand for advertising, such as

\[ p_j = \theta_1^A r_j \left( 1 - \theta_2^A \sum_{j' \in F} \omega_{j'f'} q_{j'} \right) \]  

(2.5)

where \( f \) is a format of station \( j \), \( \theta_1^A \) is a scaling factor for value of advertising, \( \theta_2^A \) is a market power indicator and \( \omega_{j'f'} \in \Omega \) are weights indicating competition closeness, between formats \( f \) and \( f' \).

The weights \( \omega \) are a key factor determining competition between formats and thus market power. They reflect the fact that some formats are further and others are closer substitutes for advertisers because of differences in the demographic composition of their listeners. In principle, one could proceed by estimating these weights from the data. However, here it is not feasible to do that because the available data do not contain radio station level advertising prices. Instead, I make additional assumptions that will enable me to compute the weights using publicly available data.

The reminder of this subsection discusses the formula for the weights and provides an example supporting this intuition. The formal micro-model is given in Appendix A.1.

Let there be \( A \) types of advertisers. Each type \( a \in A \) targets a certain demographic group(s) \( a \). I.e. advertiser of type \( a \) gets positive utility only if a listener of type \( a \) hears an ad. Denote \( r_{fa} \) to be the probability that a listener of type \( a \) chooses format \( f \) and \( r_{a|f} \) to be the probability that a random listener of format \( f \) is of type \( a \). Advertisers take these numbers, along with station ratings \( r_j \), as given and decide on which station to advertise. This assumption is is motivated by the fact that about 75% is purchased by small local firms. Such firms’ advertising decisions are unlikely to influence prices and station ratings in the short run.

This decision problem results in an inverse demand for advertising with weights \( \omega_{jj'} \), that are given by

\[ \omega_{jj'} = \frac{1}{\sum_{a \in A} r_{a|f} \sum_{a \in A} r_{a|f} r_{f'|a} r_{a|f'}} \]  

(2.6)
The formal justification and derivation of this equation is given in Appendix A.1. The intuition behind it is that the total impact on the per-listener price of an ad in format $f$ is a weighted average of impacts on the per-listener value of an ad for different types of advertisers. The weighting is done by the advertisers’ arrival rates, which are equal to the listeners’ arrival rates $r_{af}$. For each advertiser of type $a$ the change of value of an ad in format $f$, in response to a change of total quantity supplied in format $f'$, is affected by two things: it is proportional to the probability of correct targeting in format $f$, given by $r_{af}$, because advertisers are expected utility maximizers; and it is proportional to the share of advertising purchased by this advertiser in format $f'$, given by $r'_{f|a}$. Assembling these pieces together and normalizing the weights to sum to 1 gives equation (2.6).

To illustrate how these weights work in practice, consider the following example. Suppose that there are only two possible formats of programming: Talk and Hits, and two types of consumers: Teens and Adults. Teens like mostly Hits format and Adults like Talk format. However, Adults like Hits more than Teens like Talk. Hypothetical numerical values of $r_{f|a}$ and $r_{af}$ are given in Table 2.1.

<table>
<thead>
<tr>
<th></th>
<th>Talk</th>
<th>Hits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teens</td>
<td>1/5</td>
<td>4/5</td>
</tr>
<tr>
<td>Adults</td>
<td>3/5</td>
<td>2/5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Teens</th>
<th>Adults</th>
</tr>
</thead>
<tbody>
<tr>
<td>Talk</td>
<td>1/4</td>
<td>3/4</td>
</tr>
<tr>
<td>Hits</td>
<td>2/3</td>
<td>1/3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Talk</th>
<th>Hits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Talk</td>
<td>0.56</td>
<td>0.44</td>
</tr>
<tr>
<td>Hits</td>
<td>0.28</td>
<td>0.72</td>
</tr>
</tbody>
</table>

Table 2.1: Simple example of advertising weights

In Table 2.1, the impact of Hits on the price of Talk is greater than the impact of Talk on the price of Hits. This is due to the fact that the quantity supplied in the Hits format affects Adult-targeting advertisers (who drive the price of the Talk format) to a much greater extent than ad quantity in Talk affects Teen-targeting advertisers (who drive the price of the Hits format). Moreover, because the weights sum up to 1, it must be that the own effect of Talk is weaker than that of Hits. This is exactly the essence of the mechanism behind Equation (2.6). More examples from the data with an extensive discussion are given in Section 2.6.

In the next section I will combine demand for programming and advertising to
compose the profits of the radio station owners.

## 2.3.4 Radio station owners

In this subsection I will describe a profit maximizing problem for the radio station owners. It will be a version of equation (2.3) that allows for non-zero cost in selling advertising and common radio station ownership. Given the advertising quantity choices of competing owners $q_{-k}$, the profit of radio station owner $k$ is given by

$$
\bar{\pi}_k(q_k|q_{-k}, \xi, \theta) = \max_{\{q_j: j \in s_k\}} \sum_{j \in s_k} r_j(q_j|\xi, \theta^L)p_jq_j - MC_j(q_j) = 
$$

$$
= \theta_1^A \max_{\{q_j: j \in s_k\}} \sum_{j \in s_k} q_j r_j(q_j|\xi, \theta^L) \left(1 - \theta_2^A \sum_{j' \in \mathcal{F}} \omega_{jj'}^m q_{j'} \right) + C_j(q_j|\theta^A, \theta^C) (2.7)
$$

where $C_j(q_j)$ is the total cost of selling advertising. I assume constant marginal cost and allow for a firm level of unobserved cost heterogeneity $\eta_j$, i.e. $C_j(q_j|\theta^A, \theta^C) = \theta_1^A[\theta^C + \eta_j]q_j$.

I assume that the markets are in a Cournot Nash Equilibrium. The first order conditions for profit optimization become

$$
r_j p_j + \sum_{j' \in s_k} q_{j'} \left[ \frac{\partial r_{j'}}{\partial q_{j'}} p_{j'} - r_{j'} \theta_2^A \omega_{jj'}^m \right] - \theta^C - \eta_j = 0 \quad \forall k \text{ and } j \in s_k (2.8)
$$

Additionally, I assume that station unobserved quality is exogenous but serially correlated. It evolves according an AR(1) process such that

$$
\xi_j^t = \rho \xi_j^{t-1} + \zeta_j^t (2.9)
$$

where $\zeta_j^t$ is an exogenous innovation to station quality.
2.4 Data description

I have constructed a panel of data on radio stations and radio station ownership merging data from two sources: *BIA Financial Network Inc.* and *the SQAD Media Market Guide*.

BIAfn provided me data on: radio station ownership, revenues, market shares and formats. The data are a 1996-2006 panel covering each radio station in the market in 2006. The data are incomplete in the sense that I do not observe all the stations that exited the market between 1996 and 2006. According to Sweeting (2007) there were only 50 stations that exited during this period, mostly due to violations of FCC regulations. Because this number is small relative to the 11,000 stations in the sample, this omission is unlikely to significantly influence the results.

The BIAfn data are supplemented with data on aggregate advertising prices. Unfortunately, price data at the station level are not available. SQAD instead provides estimates of market prices that are obtained using proprietary formulas. According to anecdotal evidence, those estimates are widely recognized as the industry standard and are the best available data on market prices. Radio market prices are reported as a Cost per Rating Point (CPP). CPP is the cost of advertising per 1 percent of listenership. SQAD provides CPP broken down into daytime and demographic categories. We will estimate station level prices from SQAD CPPs using radio station ratings that are broken down by time of day and demographics.

An observation in my data is a radio station operating in a specific half-year and in a specific market. BIAfn and SQAD use Arbitron market definitions. An Arbitron market is in most cases a county or a metropolitan area. According to the surveys conducted by CRA International (2007) for the Canadian market (which is similar to the US market): “The majority of radio advertisers are local. They are only interested in advertising in their local area since most of their customers and potential buyers live in or very near their city.” In our analysis, I assume no interdependence between markets. To further assure that there is no overlap between markets, I use only the 88 market sub-selection that was developed in Sweeting (2007). Table 2.7 presents a list of the 88 markets, along with their populations.
Table 2.2: Panel data descriptive statistics

To achieve a sharper identification of the random effects covariance matrix, I use listenership shares of different demographic groups in each of the formats that has been aggregated from the 100 biggest markets. I observe listenership shares of different age/gender groups within each station format between 1998 and 2006, and shares for income, race and education groups between 2003 and 2006. Unfortunately, I do not observe a full matrix of market shares for all the combinations of demographic variables. For example, I do not see what the share of rock stations is among black, educated males. Instead I have shares for blacks, educated people, and males.

Table 2.2 contains some basic aggregate statistics about the industry. The top part of the table documents changes in concentration of radio station ownership. The average number of stations owned in our dataset grew from 4.43 in 1996 to 6.28 in 2006. This ownership consolidation resulted in growth of the market share of the 3 biggest owners (C3) from 77% in 1996 to 90% in 2006, peaking at 97% in 2000. The middle part of the table contains the average percentages of stations that switched owners and that switched formats. Between 1996 and 2000 more than 10% of stations switched owners yearly. After 2000 the number dropped to below 4%. Greater concentration activity in the 1996-2000 period was also associated with more format switching. The percentage of stations that switched format peaked in 1998 and 2001 at 13%.

\(^2\)Source: Arbitron Format Trends Report
CHAPTER 2. MERGERS IN TWO-SIDED MARKETS

2.5 Estimation

The estimation of the model is done in two steps. In the first step, I estimate the demand model that includes parameters of the consumer utility $\theta^L$ (see equation (2.4)) and the unobserved station quality lag parameter $\rho$ (see equation (3.1)). In the second step, we recover parameters of the inverse demand for advertising $\theta^A$, $w_{jj'}$ (see equation (2.5)) and cost parameters $\theta^C$ (see equation (2.7)).

2.5.1 First stage

This stage provides the estimates of demand for radio programming $\theta^L$. Estimation is done using the generalized method of simulated moments. I use two sets of moment conditions. The first set is based on the fact that innovation to station unobserved quality $\xi_j$ has a mean of zero conditional on the instruments:

$$E[\xi_jt - \rho\xi_{j-1} | Z_1, \theta^L] = 0$$

(2.10)

This moment condition follows Berry, Levinsohn, and Pakes (1995) and extends it by explicitly introducing auto-correlation of $\xi$. I use instruments for advertising quantity since it is likely to be correlated with unobserved station quality. My instruments include: lagged mean and second central moment of competitors’ advertising quantity, lagged market HHIs and lagged number and cumulative market share of other stations in the same format. These are valid instruments under the assumption that $\xi_t$ follows an AR(1) process and the fact that decisions about portfolio selection are made before decisions about advertising.

A second set of moment conditions is based on demographic listenership data. Let $R_{fc}$ be the national market share of format $f$ among listeners possessing certain demographic characteristics $c$. The population moment conditions are

$$\int \int_{(D_{ic}, m)} \nu_i \frac{\exp[\delta_{ji} + \mu_{mt}]}{\sum_{j' \in s_{mt}} \exp[\delta_{ji'} + \mu_{ji'}]} dF^t(\nu_i) dF^c(D_{ic}, m) dt = R_{fc}$$

(2.11)

where $F_c^t(D_i, m)$ is a national distribution of people who possess characteristic $c$ at
time $t$. Each person is characterized by the demographic characteristics $D_i$ and the market $m$ they belong to.

For each time $t$ and demographic characteristic $c$, I draw $I$ observation pairs $(D_{ic}^t, m)$ from the nationally aggregated CPS. Let $g = (g_1, g_2)$ represent the empirical moments and $W$ be a weighting matrix. I estimate the model by using the constrained optimization procedure:

$$\min_{\theta^L, \xi, g} g'Wg$$

Subject to:

$$\hat{r}_{jmt}(q_{mt}|s_{mt}, \xi_{mt}, d_{mt}, \theta^L) = r_{jmt} \quad \forall t, m$$

$$\frac{1}{TI} \sum_t \sum_{(D_{ic}^t, m)} \int \frac{\exp[\delta_{jmt} + \mu_{jmi}]}{\sum_{j' \in s_{mt}} \exp[\delta_{j'mt} + \mu_{j'mi}]} dF(\nu_i) - R_{fc} = g_1 \quad \forall c$$

$$\frac{1}{\text{size of } \xi} Z_1(\xi - \rho L \xi) = g_2$$

where $L$ is a lag operator that converts the vector $\xi$ into one-period lagged values. If the radio station did not exist in the previous period, the lag operator has a value of zero. Integration with respect to demographics when calculating the first constraint is obtained by drawing from the CPS in the particular market and period. This way of integrating allows us to maintain proper correlations between possessed demographic characteristics. The same is true when obtaining the data set $D_{ic}^t$. When computing the interaction terms $\mu$ in the second constraint, I draw one vector $\nu_i$ from the normal distribution for each $D_{ic}^t$.

### 2.5.2 Second stage

The second stage of the estimation obtains the competition matrix $\Omega$ and the parameters of demand for advertising $\theta^A$. The estimation is done separately for every market, thereby allowing for different $\Omega$ and $\theta^A$.

To compute the matrices $\Omega^m$ for each market I use the specification layed out in
section 2.3.3. The elements of the matrix $\Omega$ are specified as

$$
\omega_{ff'} = \frac{1}{\sum_{a \in A} r_a^2 \sum_{a \in A} r_{a|f} r_{f'|a}}
$$

following equation (2.6). The $r_{f|a}$ are advertisers’ beliefs about listeners’ preferences for formats. These are constant across markets. To recognize that advertisers know the demographic composition of each market I allow for market specific listener arrival rates for each format $r_{f|a}^m$. However, I assume that the advertisers compute those values by using Radio Today reports and the Current Population Survey. After computing weights, I treat $\Omega^m$ as exogenous and fixed in all of the following steps.

After computing matrices $\Omega$, I estimate $\theta^A$. Using estimates of demand for radio programming $\theta^L$ from the first stage, I compute ratings for each station conditioned on the counterfactual advertising quantities. I use the set of $3M$ moment conditions

$$
E_m[\eta^m[Z_2, \theta^A, \theta^C]] = 0 \quad \forall m \in M
$$

where the integral is taken with respect to time and stations in each market. $\eta^{tm}_j$ is an unobserved shock to marginal cost defined in equation (2.5). The $Z_2$ are three instruments: a column of ones, the AM/FM dummy and number of competitors in the same format. They are uncorrelated with $\eta^m$ under the IID assumption, but are correlated with the current choice of quantity because they describe the market structure.

We back out $\eta^{tm}_j$ using FOCs for owner’s profit maximization (see equation (2.7))

$$
\eta^{t}_j = r^t_j p^t_j + \sum_{j' \in s^t_k} q^{t}_{j'} \left[ \frac{\partial r^t_{j'}}{\partial q^{t}_{j'}} p^t_{j'} - \theta^A_{2m} r^t_{j'} \omega^m_{ff'} \right] - \theta^C_{m} \forall t \in T, k \in K^{tm}, j \in s^{tm}_k
$$

Since the equation does not depend on $\theta^A_{1m}$, I can use it to estimate $\theta^A_{2m}$ and $\theta^C_{m}$. During the estimation, I allow for a different value of marginal cost for each market. I allow

---

3Such an approach potentially ignores possible variance of the $\Omega^m$ estimator. The source of this variance might come from the finiteness of the CPS dataset and the distribution of Arbitron estimates.
for 3 different values for the slope of inverse demand depending on the population of the market (up to 500 people, between 500 and 1500, and 1500 or more). Ratings and derivatives of ratings in the equation (2.14) are calculated using the estimates of $\theta^L$ and $\xi$ from the first stage. Demographic draws are taken from the CPS and are independent of those used in the first stage. Given the estimates of $\theta^A_{2m}$ and $\theta^C$, I can back out $\theta^A_{1m}$ by equating the observed average revenue in each market with its predicted counterpart.

Next I discuss a variation in the data that identifies parameters $\theta^A$ and $\theta^C$. The intuition for such identification is that estimating Equation 2.14 can be regarded as a linear regression in which $\theta^C_m$ is an intercept and $\theta^A_2$ is a coefficient of a variable that is a function of supplied quantity. In this case, the mean deviation of FOCs from zero in each market identifies the intercept $\theta^C_m$. The slope parameter $\theta^A_2$ is identified by the size of the response of the firm to changes in quantity supplied by its competitors due to change in the market structure or demographics. Such a response, as mentioned in Section 2.3, is composed of listeners’ demand feedback and the direct effect of quantity on CPP. Elasticity of listeners’ demand, that determines the strength of the feedback, is consistently estimated in the first step. Therefore, one can subtract the difference out the feedback effect from the total response observed in the data. This allows to obtain the strength of the direct effect that directly identifies the slope of the CPP, $\theta^A_2$. For example, if we look at the response of ad quantity reacting to the merger, the slope of listeners’ demand alone predicts large increases in ad quantity. However in the data, we observe smaller increases or even decrease in the quantity supplied, depending on the market. Those differences are rationalized by a negative value of CPP slope, $\theta^A_2$.

2.6 Results

This section presents estimates of the structural parameters. The next subsection discusses listeners’ demand parameters. This is followed by results concerning advertisers’ demand and market power. The last subsection contains estimates of marginal cost and profit margin (before subtracting fixed cost).
2.6.1 Listeners’ demand

Table 2.3 contains estimates of demand parameters for radio programming. The estimate of the mean effect of advertising on listeners’ utility is negative and statistically significant. This is consistent with the belief that radio listeners have a disutility for advertising. When it comes to the mean effects of programming formats, Contemporary Hit Radio format gives the most utility, while the News/Talk format gives the least.

The second column of Table 2.3 contains variances of random effects for station formats. The higher a format’s variance, the more persistent are the tastes of listeners for that format. For example, in response to an increased amount of advertising, if the variance of the random effect for that format is high, listeners tend to switch to a station of the same format. The estimates also suggest that tastes for the Alternative/Urban format are the most persistent.

Table 2.4 contains estimates of interactions between listener characteristics and format dummies. The majority of the parameters are consistent with intuition. For example, younger people are more willing to choose a CHR format while older people go for News/Talk. The negative coefficients on the interaction of Hispanic format with education and income suggests that less educated Hispanic people with lower income are more willing to listen to Hispanic stations. For blacks, I find a disutility for Country, Rock and Hispanic, and a high utility for Urban. This is consistent with the the fact that Urban radio stations play mostly rap, hip-hop and soul music performed by black artists.

2.6.2 Advertisers’ demand

Tables 2.5 presents the weights for selected markets representing large, medium and small listener populations. They were computed using the 1999 edition of Radio Today publication and Common Population Survey aggregated from 1996 to 2006. It is interesting to compute a total impact coefficient that is the sum of all the columns of the table for each format. Not surprisingly, general interest formats like AC and News/Talk have the biggest impact on the price of advertising, while Spanish
### Table 2.3: Estimates of mean and random effects of demand for radio programming.

Stars indicate parameter significance when testing with 0.1, 0.05 and 0.01 test sizes.

<table>
<thead>
<tr>
<th></th>
<th>Mean Effects ($\theta_{1i}^j$)</th>
<th>Random Effects ($\Sigma_1$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advertising</td>
<td>$-1.106^{***}$</td>
<td>$0.030^{***}$</td>
</tr>
<tr>
<td>AM/FM</td>
<td>$0.861^{***}$</td>
<td>$-$</td>
</tr>
<tr>
<td></td>
<td>$(-0.002)$</td>
<td>$(-0.009)$</td>
</tr>
<tr>
<td></td>
<td>$(-0.000)$</td>
<td></td>
</tr>
<tr>
<td>AC, SmoothJazz, and New AC</td>
<td>$-2.431^{***}$</td>
<td>$0.043^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(-0.008)$</td>
<td>$(-0.004)$</td>
</tr>
<tr>
<td>Rock</td>
<td>$-1.559^{***}$</td>
<td>$0.004$</td>
</tr>
<tr>
<td></td>
<td>$(-0.140)$</td>
<td>$(-0.020)$</td>
</tr>
<tr>
<td>CHR</td>
<td>$-0.179^{***}$</td>
<td>$0.009^*$</td>
</tr>
<tr>
<td></td>
<td>$(-0.025)$</td>
<td>$(-0.006)$</td>
</tr>
<tr>
<td>Alternative Urban</td>
<td>$-2.339^{***}$</td>
<td>$0.348^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(-0.026)$</td>
<td>$(-0.008)$</td>
</tr>
<tr>
<td>News/Talk</td>
<td>$-4.678^{***}$</td>
<td>$0.024^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(-0.010)$</td>
<td>$(-0.002)$</td>
</tr>
<tr>
<td>Country</td>
<td>$-2.301^{***}$</td>
<td>$0.011^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(-0.006)$</td>
<td>$(-0.003)$</td>
</tr>
<tr>
<td>Spanish</td>
<td>$-1.619^{***}$</td>
<td>$0.011^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(-0.004)$</td>
<td>$(-0.001)$</td>
</tr>
<tr>
<td>Other</td>
<td>$-4.657^{***}$</td>
<td>$0.005^{**}$</td>
</tr>
<tr>
<td></td>
<td>$(-0.004)$</td>
<td>$(-0.002)$</td>
</tr>
<tr>
<td>$\rho$</td>
<td>$0.568^{***}$</td>
<td>$-$</td>
</tr>
<tr>
<td></td>
<td>$(-0.091)$</td>
<td></td>
</tr>
</tbody>
</table>
format has the smallest. The values on the diagonals of the matrices represent the formats’ own effect of the quantity of advertising supplied on per-listener price. They are usually bigger than the off-diagonal values, that suggests that it is mostly the ad quantity in the same format that influences a per-listener price. In accord with an intuition, the formats with the most demographically homogenous listener pools, Urban/Alternative and Spanish, have the highest values of the own effects. On the other hand, general interest formats like CHR and Rock are characterized by the smallest values of the own effect, measuring the fact that their target population of listeners is more dispersed across other formats. For cross effects, one notices that News/Talk is close to AC and Urban is close to CHR. This can be explained by, for example, the age of the listeners. In the former case the formats appeal to an older population while in the latter case to a younger one.

 Estimates of the slope of inverse demand are presented in Table 2.6. In markets with less than 0.5m people radio stations have considerable control over the per-listener price. However, such control significantly drops in markets from 0.5m

<table>
<thead>
<tr>
<th></th>
<th>Demographics characteristics (II)</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age</td>
<td>Sex</td>
<td>Education</td>
<td>Income</td>
<td>Black</td>
<td>Spanish</td>
</tr>
<tr>
<td>AC, SmoothJazz, and New AC</td>
<td>−0.171***</td>
<td>−0.341***</td>
<td>0.602***</td>
<td>−0.024***</td>
<td>0.121***</td>
<td>−1.014***</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.064)</td>
<td>(0.013)</td>
<td>(0.003)</td>
<td>(0.012)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>Rock</td>
<td>−0.645***</td>
<td>0.399***</td>
<td>0.861***</td>
<td>−0.147***</td>
<td>−1.359***</td>
<td>−1.643***</td>
</tr>
<tr>
<td>(0.072)</td>
<td>(0.031)</td>
<td>(0.006)</td>
<td>(0.045)</td>
<td>(0.007)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>CHR</td>
<td>−2.541***</td>
<td>0.477***</td>
<td>1.772***</td>
<td>−0.291***</td>
<td>1.946***</td>
<td>0.463***</td>
</tr>
<tr>
<td>(0.015)</td>
<td>(0.080)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.015)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Alternative Urban</td>
<td>−0.817***</td>
<td>1.350***</td>
<td>0.583***</td>
<td>−0.141***</td>
<td>3.152***</td>
<td>0.267***</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.018)</td>
<td>(0.025)</td>
<td>(0.002)</td>
<td>(0.005)</td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td>News/Talk</td>
<td>0.329***</td>
<td>1.228***</td>
<td>0.237***</td>
<td>0.093***</td>
<td>−0.321***</td>
<td>−1.649***</td>
</tr>
<tr>
<td>(0.002)</td>
<td>(0.012)</td>
<td>(0.009)</td>
<td>(0.005)</td>
<td>(0.001)</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Country</td>
<td>0.002***</td>
<td>−0.149***</td>
<td>0.133***</td>
<td>−0.125***</td>
<td>−1.548***</td>
<td>−1.717***</td>
</tr>
<tr>
<td>(0.004)</td>
<td>(0.022)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.009)</td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Spanish</td>
<td>−0.024***</td>
<td>−0.908***</td>
<td>−0.328***</td>
<td>−1.140***</td>
<td>−2.560***</td>
<td>0.797***</td>
</tr>
<tr>
<td>(0.013)</td>
<td>(0.012)</td>
<td>(0.018)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>0.263</td>
<td>0.624***</td>
<td>0.338***</td>
<td>−0.031</td>
<td>0.498***</td>
<td>0.238***</td>
</tr>
<tr>
<td>(0.373)</td>
<td>(0.003)</td>
<td>(0.006)</td>
<td>(0.063)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.4: Interaction terms between listeners’ demographics and taste for radio programming.
### Los Angeles, CA

<table>
<thead>
<tr>
<th></th>
<th>AC SmoothJazz</th>
<th>Rock</th>
<th>CHR</th>
<th>Alternative Urban</th>
<th>News/Talk</th>
<th>Country</th>
<th>Spanish</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC SmoothJazz New AC</td>
<td><strong>0.22</strong></td>
<td>0.10</td>
<td>0.11</td>
<td>0.09</td>
<td>0.17</td>
<td>0.14</td>
<td>0.00</td>
<td>0.17</td>
</tr>
<tr>
<td>Rock</td>
<td>0.15</td>
<td><strong>0.21</strong></td>
<td>0.12</td>
<td>0.09</td>
<td>0.16</td>
<td>0.13</td>
<td>0.01</td>
<td>0.12</td>
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<td>CHR</td>
<td>0.18</td>
<td>0.12</td>
<td><strong>0.16</strong></td>
<td>0.16</td>
<td>0.10</td>
<td>0.13</td>
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<td>0.13</td>
</tr>
<tr>
<td>Alternative Urban</td>
<td>0.11</td>
<td>0.05</td>
<td>0.17</td>
<td><strong>0.44</strong></td>
<td>0.06</td>
<td>0.05</td>
<td>0.00</td>
<td>0.12</td>
</tr>
<tr>
<td>News/Talk</td>
<td>0.17</td>
<td>0.10</td>
<td>0.05</td>
<td>0.05</td>
<td><strong>0.30</strong></td>
<td>0.13</td>
<td>0.00</td>
<td>0.21</td>
</tr>
<tr>
<td>Country</td>
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<td>0.09</td>
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<td>0.15</td>
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<td>0.01</td>
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<td>Spanish</td>
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<td>0.01</td>
<td>0.03</td>
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<tr>
<td>Other</td>
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<td>0.06</td>
<td>0.08</td>
<td>0.20</td>
<td>0.17</td>
<td>0.00</td>
<td><strong>0.23</strong></td>
</tr>
<tr>
<td>Total impact</td>
<td><strong>1.20</strong></td>
<td>0.79</td>
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<td>1.15</td>
<td>1.00</td>
<td>0.77</td>
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</tr>
</tbody>
</table>

### Atlanta, GA

<table>
<thead>
<tr>
<th></th>
<th>AC SmoothJazz</th>
<th>Rock</th>
<th>CHR</th>
<th>Alternative Urban</th>
<th>News/Talk</th>
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<th>Spanish</th>
<th>Other</th>
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<td>0.14</td>
<td>0.18</td>
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<td>0.18</td>
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<td>0.12</td>
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<td>0.09</td>
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</tr>
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<td>0.10</td>
<td>0.05</td>
<td>0.05</td>
<td><strong>0.25</strong></td>
<td>0.17</td>
<td>0.00</td>
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<tr>
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<td>0.08</td>
<td>0.06</td>
<td>0.13</td>
<td><strong>0.26</strong></td>
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<tr>
<td>Spanish</td>
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<td>0.01</td>
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<td>0.07</td>
<td>0.20</td>
<td>0.17</td>
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<td><strong>0.25</strong></td>
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<tr>
<td>Total impact</td>
<td><strong>1.11</strong></td>
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<td>0.95</td>
<td>1.31</td>
<td>0.75</td>
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### Knoxville, TN

<table>
<thead>
<tr>
<th></th>
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<th>CHR</th>
<th>Alternative Urban</th>
<th>News/Talk</th>
<th>Country</th>
<th>Spanish</th>
<th>Other</th>
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</thead>
<tbody>
<tr>
<td>AC SmoothJazz New AC</td>
<td><strong>0.20</strong></td>
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<td>0.11</td>
<td>0.10</td>
<td>0.16</td>
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<tr>
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<td>0.10</td>
<td>0.18</td>
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<tr>
<td>CHR</td>
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<td>0.12</td>
<td><strong>0.18</strong></td>
<td>0.14</td>
<td>0.08</td>
<td>0.17</td>
<td>0.02</td>
<td>0.13</td>
</tr>
<tr>
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<td>0.16</td>
<td><strong>0.38</strong></td>
<td>0.06</td>
<td>0.08</td>
<td>0.00</td>
<td>0.13</td>
</tr>
<tr>
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<td>0.16</td>
<td>0.13</td>
<td>0.10</td>
<td>0.09</td>
<td><strong>0.17</strong></td>
<td>0.16</td>
<td>0.01</td>
<td>0.18</td>
</tr>
<tr>
<td>Country</td>
<td>0.15</td>
<td>0.13</td>
<td>0.14</td>
<td>0.10</td>
<td>0.09</td>
<td><strong>0.22</strong></td>
<td>0.01</td>
<td>0.16</td>
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<tr>
<td>Spanish</td>
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<td>0.05</td>
<td>0.11</td>
<td>0.02</td>
<td>0.02</td>
<td>0.04</td>
<td><strong>0.66</strong></td>
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</tr>
<tr>
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<td>0.12</td>
<td>0.12</td>
<td>0.18</td>
<td>0.01</td>
<td><strong>0.21</strong></td>
</tr>
<tr>
<td>Total impact</td>
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<td>0.90</td>
<td>1.11</td>
<td>1.05</td>
<td>0.74</td>
<td>1.21</td>
<td>0.72</td>
<td>1.14</td>
</tr>
</tbody>
</table>

Table 2.5: Product closeness matrices for chosen markets

to 2m people, and it disappears completely in markets with more than 2m people, making radio stations essentially price takers. I suspect that this phenomenon can be
explained by the fact that in larger markets there are more outside options for radio advertising. This can lead to tougher competition between media outlets, and make the inverse demand for advertising flatter. However, in small markets radio might be a primary advertising channel, because other media like the Internet or billboards are not as widespread. This gives radio stations more control over price.

### 2.6.3 Supply

The marginal costs of selling advertising minutes are presented in Table 2.7. The values of this cost range from $356 per minute of advertising sold in Los Angeles, CA to $11 in Ft. Myers, FL. 66% of the variation in marginal cost can be explained by variation in market population. A population increase of one thousand translates to about a 2 cent increase in marginal cost (with t-stat equal to 12). The high correlation between population and marginal costs can be explained by the fact that revenues per-minute of advertising are an increasing function of total market population. Suppose this surplus is split between radio station owners and advertisers’ sales people according to the Nash Bargaining solution. In this case, the high correlation of revenue with population will translate into a high correlation of marginal cost with population.

From the revenues and marginal cost estimates, I can calculate variable profit margins. These are presented in the last column of Table 2.7. The range is from 92% in Shreveport, LA to 15% in Honolulu, HI and Reno, NV. It is interesting that 38% of the profit margin variation can be explained by the variance in total ad quantity supplied and markets with high profit margins firms supply more advertising. The marginal effect of extra minute per day of broadcasted advertising translates into 0.6% of extra profit margin.
<table>
<thead>
<tr>
<th>Market</th>
<th>Population (mil)</th>
<th>Marginal cost ($ per-minute)</th>
<th>Profit margin</th>
<th>Market</th>
<th>Population</th>
<th>Marginal cost</th>
<th>Profit margin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Los Angeles, CA</td>
<td>13.155</td>
<td>358.4 (5.15)</td>
<td>30%</td>
<td>Tulsa, OK</td>
<td>856</td>
<td>72.8 (2.13)</td>
<td>21%</td>
</tr>
<tr>
<td>Chicago, IL</td>
<td>9.341</td>
<td>180.0 (2.70)</td>
<td>34%</td>
<td>Knoxville, TN</td>
<td>785</td>
<td>54.3 (1.99)</td>
<td>27%</td>
</tr>
<tr>
<td>Dallas-Ft. Worth, TX</td>
<td>5.847</td>
<td>198.6 (5.60)</td>
<td>28%</td>
<td>Albuquerque, NM</td>
<td>740</td>
<td>27.4 (1.04)</td>
<td>36%</td>
</tr>
<tr>
<td>Houston-Galveston, TX</td>
<td>5.279</td>
<td>199.7 (4.20)</td>
<td>28%</td>
<td>Ft. Myers-Naples-Marco Island, FL</td>
<td>737</td>
<td>11.3 (0.94)</td>
<td>57%</td>
</tr>
<tr>
<td>Atlanta, GA</td>
<td>4.710</td>
<td>95.4 (3.37)</td>
<td>43%</td>
<td>Omaha-Council Bluffs, NE-IA</td>
<td>728</td>
<td>48.0 (0.91)</td>
<td>28%</td>
</tr>
<tr>
<td>Boston, MA</td>
<td>4.532</td>
<td>172.2 (3.68)</td>
<td>33%</td>
<td>Harrisburg-Lebanon-Carlisle, PA</td>
<td>649</td>
<td>29.7 (1.44)</td>
<td>42%</td>
</tr>
<tr>
<td>Miami-Ft, FL</td>
<td>4.174</td>
<td>134.3 (3.70)</td>
<td>28%</td>
<td>El Paso, TX</td>
<td>619</td>
<td>41.8 (4.12)</td>
<td>20%</td>
</tr>
<tr>
<td>Seattle-Tacoma, WA</td>
<td>3.776</td>
<td>128.7 (2.21)</td>
<td>29%</td>
<td>Quad Cities, IA-IL</td>
<td>618</td>
<td>51.3 (1.30)</td>
<td>23%</td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>3.638</td>
<td>63.7 (1.84)</td>
<td>39%</td>
<td>Wichita, KS</td>
<td>598</td>
<td>38.9 (0.85)</td>
<td>25%</td>
</tr>
<tr>
<td>Minneapolis-St. Paul, MN</td>
<td>3.155</td>
<td>160.8 (4.66)</td>
<td>26%</td>
<td>Little Rock, AR</td>
<td>577</td>
<td>45.2 (1.64)</td>
<td>26%</td>
</tr>
<tr>
<td>St. Louis, MO</td>
<td>2.689</td>
<td>190.6 (5.38)</td>
<td>18%</td>
<td>Columbia, SC</td>
<td>577</td>
<td>60.0 (2.10)</td>
<td>23%</td>
</tr>
<tr>
<td>Tampa-St, FL</td>
<td>2.649</td>
<td>102.7 (2.09)</td>
<td>26%</td>
<td>Charleston, SC</td>
<td>569</td>
<td>59.6 (1.74)</td>
<td>19%</td>
</tr>
<tr>
<td>Denver-Boulder, CO</td>
<td>2.604</td>
<td>99.9 (1.40)</td>
<td>32%</td>
<td>Des Moines, IA</td>
<td>564</td>
<td>21.3 (0.92)</td>
<td>40%</td>
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<td>2.352</td>
<td>48.6 (1.35)</td>
<td>41%</td>
<td>Spokane, WA</td>
<td>540</td>
<td>24.5 (0.63)</td>
<td>28%</td>
</tr>
<tr>
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<td>2.134</td>
<td>170.6 (3.34)</td>
<td>24%</td>
<td>Madison, WI</td>
<td>520</td>
<td>93.6 (3.02)</td>
<td>22%</td>
</tr>
<tr>
<td>Charlotte, NC-SC</td>
<td>2.127</td>
<td>67.1 (1.96)</td>
<td>38%</td>
<td>Augusta, GA</td>
<td>510</td>
<td>30.9 (0.60)</td>
<td>24%</td>
</tr>
<tr>
<td>Sacramento, CA</td>
<td>2.100</td>
<td>47.6 (1.30)</td>
<td>42%</td>
<td>Pt. Wayne, IN</td>
<td>509</td>
<td>37.8 (1.35)</td>
<td>27%</td>
</tr>
<tr>
<td>Salt Lake City, UT</td>
<td>1.924</td>
<td>58.1 (1.19)</td>
<td>26%</td>
<td>Lexington-Fayette, KY</td>
<td>495</td>
<td>36.8 (1.59)</td>
<td>35%</td>
</tr>
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<td>1.900</td>
<td>75.0 (2.27)</td>
<td>24%</td>
<td>Chattanooga, TN</td>
<td>471</td>
<td>41.5 (2.53)</td>
<td>29%</td>
</tr>
<tr>
<td>Kansas City, MO-KS</td>
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<td>152.5 (2.87)</td>
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<td>Boise, ID</td>
<td>469</td>
<td>46.2 (3.73)</td>
<td>30%</td>
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<td>47.7 (1.49)</td>
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<td>453</td>
<td>18.6 (2.03)</td>
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<td>99.7 (1.64)</td>
<td>15%</td>
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<td>38.1 (2.48)</td>
<td>46%</td>
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<td>55%</td>
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<td>38%</td>
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<td>276</td>
<td>34.4 (2.29)</td>
<td>26%</td>
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<td>32%</td>
<td>Binghamton, NY</td>
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<td>37.5 (1.51)</td>
<td>27%</td>
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<td>57.7 (1.98)</td>
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<td>25%</td>
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<td>75.6 (1.35)</td>
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<td>Medford-Ashland, OR</td>
<td>184</td>
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<td>21%</td>
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<td>26%</td>
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<td>31.6 (2.77)</td>
<td>28%</td>
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<td>Honolulu, HI</td>
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<td>Williamsport, PA</td>
<td>130</td>
<td>31.0 (1.13)</td>
<td>23%</td>
</tr>
<tr>
<td>Albany, NY</td>
<td>0.909</td>
<td>113.9 (3.18)</td>
<td>16%</td>
<td>Monroe, LA</td>
<td>124</td>
<td>14.2 (1.49)</td>
<td>64%</td>
</tr>
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<td>0.902</td>
<td>24.5 (0.67)</td>
<td>24%</td>
<td>Sioux City, IA</td>
<td>118</td>
<td>26.1 (0.96)</td>
<td>24%</td>
</tr>
<tr>
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<td>41.1 (0.93)</td>
<td>27%</td>
<td>San Angelo, TX</td>
<td>104</td>
<td>26.4 (1.36)</td>
<td>16%</td>
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<tr>
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<td>38%</td>
<td>Bismarck, ND</td>
<td>99</td>
<td>32.8 (1.65)</td>
<td>22%</td>
</tr>
</tbody>
</table>

Table 2.7: Estimated marginal cost (in dollars per minute of broadcasted advertising) and profit margins (before subtracting the fixed cost) for a chosen set of markets
CHAPTER 2. MERGERS IN TWO-SIDED MARKETS

In this section I investigate the impact of consolidation on listener and advertiser welfare. First, I investigate the changes in the surplus of listeners and advertisers. In particular, I calculate how much market power was exercised on both of those groups. Second, I decompose market power into a variety component and extra market power that is manifested in changes in quantity supplied.

Before performing counterfactual calculations, consider descriptive relationships between concentration and prices. First, I regressed market Price Per Rating Point on a market’s HHI, including market fixed effects. I find that higher concentration is correlated with higher prices in the advertising market, suggesting that radio station owners are exercising some amount of market power on advertisers. Second, I regressed total advertising supplied on the market’s HHI with market dummies. Here I get a coefficient of 1.65(0.3). This is evidence of market power in the listener market. Because market power appears to be present in both market segments, I cannot definitely conclude who had more surplus extracted by radio station owners if I just use quantities and prices. In the next subsection I present the structural counterfactuals that answer this question.

### 2.7 Counterfactual experiments

#### 2.7.1 Impact of mergers on consumer surplus

To isolate the impact of the Telecom Act on a surplus division between advertisers and listeners, I perform a counterfactual in which I recompute new equilibrium ad quantities under the old 1996 ownership structure and 1996 formats. This calculation

<table>
<thead>
<tr>
<th>Impact of ownership change and format switching</th>
<th>Consumer surplus</th>
<th>Average ad load</th>
<th>Advertiser surplus</th>
<th>Advertising minutes</th>
<th>Mean price index</th>
</tr>
</thead>
<tbody>
<tr>
<td>No ad adjustment</td>
<td>6.6pdm</td>
<td>-6.4pdm</td>
<td>-158.3m</td>
<td>-2.491min</td>
<td>+0.60%</td>
</tr>
<tr>
<td></td>
<td>+1.3%</td>
<td>-12.6%</td>
<td>-16.3%</td>
<td>-1.5%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-1.9pdm</td>
<td>1.6pdm</td>
<td>-146.1m</td>
<td>-9.88min</td>
<td>-2.09%</td>
</tr>
<tr>
<td></td>
<td>-0.4%</td>
<td>+3.6%</td>
<td>-18.0%</td>
<td>-5.9%</td>
<td></td>
</tr>
<tr>
<td>Total impact of ownership change and format switching and ad adjustment</td>
<td>4.7pdm</td>
<td>-4.8pdm</td>
<td>-304.4m</td>
<td>-12.329min</td>
<td>+2.67%</td>
</tr>
<tr>
<td></td>
<td>+0.9%</td>
<td>-9.5%</td>
<td>-31.4%</td>
<td>-7.3%</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.8: Counterfactuals for all markets
is motivated by the fact that in 1996 many markets were at their ownership caps. The total impact of consolidation on advertiser and listener welfare is presented in the last row of Table 2.8. It turns out that mergers decreased total ad quantity by roughly 14 thousand minutes. That resulted in lowering average ad exposure by 4.8 persons-day-minutes (pdm), which is about 10% of the total ad load. The changes translated to about a 4.7 pdm increase in consumer welfare. Because we do not observe dollar prices in the listenership market we cannot compute the dollar value of this compensating variation. However, we can compute a rough estimate using the prices for the satellite radio. If we assume people buy satellite radio just to avoid advertising, we get a rough estimate of 1.5 cents per minute, or 730 million dollars for each person-day-minute per year. The total effect would amount to $3.5b. This is of course a very loose upper bound on the overall welfare gain, however if make a conservative assumption that only 10% of the value of satellite radio is lack of advertising, we get $350m.

For advertisers, a decrease in quantity supplied leads to about 2.57% increase in

<table>
<thead>
<tr>
<th>Impact of ownership change and format switching</th>
<th>Consumer surplus</th>
<th>Average ad load</th>
<th>Advertiser surplus</th>
<th>Advertising minutes</th>
<th>Mean price index</th>
</tr>
</thead>
<tbody>
<tr>
<td>No ad adjustment</td>
<td>11.7pdm</td>
<td>-5.4pdm</td>
<td>-118.1m</td>
<td>-737min</td>
<td>+1.34%</td>
</tr>
<tr>
<td></td>
<td>+2.5%</td>
<td>-17.3%</td>
<td>-15.8%</td>
<td>-1.0%</td>
<td></td>
</tr>
<tr>
<td>Impact of ad adjustment</td>
<td>1.2pdm</td>
<td>-2.2pdm</td>
<td>-119.4m</td>
<td>-8.216min</td>
<td>+5.66%</td>
</tr>
<tr>
<td></td>
<td>+0.3%</td>
<td>-8.4%</td>
<td>-19.0%</td>
<td>-11.7%</td>
<td></td>
</tr>
<tr>
<td>Total impact of ownership change</td>
<td>12.9pdm</td>
<td>-7.5pdm</td>
<td>-237.5m</td>
<td>-8.953min</td>
<td>+6.99%</td>
</tr>
<tr>
<td>format switching and ad adjustment</td>
<td>+2.8%</td>
<td>-24.2%</td>
<td>-31.8%</td>
<td>-12.6%</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.9: Counterfactuals for small markets (less than 500k people)
per-listener prices, or a $300m decrease in advertiser surplus. I therefore conclude that the Telecom Act lead to a reallocation of surplus from advertisers to listenerss. Moreover, because the gain by listeners ($350m) is larger than the surplus lost by advertisers, I find that the Act created new surplus. This increase can be explained by the fact that listeners are more annoyed by ads than the value of an ad to the advertisers.

A deeper story can be told by looking separately at small versus large markets. As mentioned in the previous section, radio stations have considerable control over prices in small markets, and no control in the large markets. Motivated by this fact, I present counterfactuals for markets with less than 0.5 population and more than 2m population. In smaller markets (see Table 2.9), stations contract advertising to exercise market power on advertisers. They supply more than 10,000 minutes less of advertising. That translates into a 7.3pdm decrease in ad exposure, which increases consumer surplus by 11.6pdm. However, prices rise by 6.4%, and cause a $230m loss in advertiser surplus. On the other hand in large markets (see Table 2.10) firms supply more than 2,000 extra minutes of advertising, which lowers consumer surplus by almost 2pdm. On balance, this does not affect advertiser surplus. I conclude that listeners gained from the Telecom Act only in small markets.

2.7.2 Effects of product variety and market power

Berry and Waldfogel (2001) suggest that the negative effects of ownership consolidation on listeners might be mitigated by format switching. They find that post-merger repositioning results in spatial competition leading to more variety, which they assume is beneficial for the listeners\(^4\). To quantify this effect, I compare surpluses computed imposing 1996 ownership and formats with surpluses computed imposing actual ownership and formats without ad quantity adjustments. That is, I fix ad quantities computed with 1996 ownership and formats. The results of this experiment are presented in the first row of Table 2.8. It turns out that if I do not account for quantity changes, the assertion of Berry and Waldfogel (2001) is true. In this

\(^4\)Similar results obtained using direct analysis of station playlists can be found in Sweeting (2008).
case, listeners have a 1.3% larger surplus (about 6.6pdm) after consolidation and format switching. Listener surplus grows because of two factors: increased variety and decreased advertising exposure. The latter decreased even though I keep number of ad minutes fixed. However, in the real world, repositioning changes firms’ incentives to set ad quantity, because it softens competition in the advertising market. The impact of quantity readjustments is presented in the middle row of Table 2.8. It turns out that both listeners and advertisers are worse off due to quantity adjustments. Listeners lose 1.9pdm and advertisers lose additional $150m in surplus.

2.8 Robustness analysis

This section examines the robustness of my advertising model to different assumptions about competition among station formats. This step is motivated by the fact that the data concerning advertiser deals is incomplete. I deal with the incompleteness by proposing a stylized decision model for advertisers that uses publicly available data to predict substitution patterns between formats. These patterns directly determine the market power of stations over advertisers, and can potentially alter the results of counterfactual experiments.

To investigate the robustness of the results, I reestimated the model under two alternative assumptions. The first scenario represents the extreme situation in which formats compete only between themselves. In particular, suppose that advertiser types get utility from only one particular format. In this case, equation (2.6) has $\omega_{ff} = 1$ and $\omega_{ff'} = 0$ if $f \neq f'$. The second scenario represents another extreme in which formats are perfect substitutes, i.e., there is only one type of advertiser who values all formats in the same way. Formally this means that $\omega_{ff'} = 1/8$, because there are 8 possible formats. The estimated model is in a sense in-between the these extreme alternatives, because it assumes that formats are imperfect substitutes.

Estimates of the inverse demand advertising slopes are presented in Table 2.11. The estimates show that the baseline model lies between the two extremes. When we assume oligopoly within a format, the estimated slope parameter $\theta_L^3$ is smaller than the one in the baseline model. On the other hand in the perfect substitutes model,
CHAPTER 2. MERGERS IN TWO-SIDED MARKETS

<table>
<thead>
<tr>
<th>Market population</th>
<th>less than .5m</th>
<th>between .5m and 1.5m</th>
<th>more than 1.5m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline model</td>
<td>1.34 (0.046)</td>
<td>0.35 (0.026)</td>
<td>0.00 (0.008)</td>
</tr>
<tr>
<td>Oligopoly within format</td>
<td>1.07 (0.036)</td>
<td>0.28 (0.061)</td>
<td>0.02 (0.009)</td>
</tr>
<tr>
<td>Perfect substitutes</td>
<td>1.44 (0.035)</td>
<td>0.32 (0.030)</td>
<td>0.01 (0.009)</td>
</tr>
</tbody>
</table>

Table 2.11: Slope of the inverse demand for ads $\theta_A^2$, by market size

<table>
<thead>
<tr>
<th>Model</th>
<th>Consumer surplus</th>
<th>Average ad load</th>
<th>Advertiser surplus</th>
<th>Advertising minutes</th>
<th>Mean price index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline model</td>
<td>4.7pdm</td>
<td>-4.8pdm</td>
<td>-304.3m</td>
<td>-12,329min</td>
<td>+2.67%</td>
</tr>
<tr>
<td></td>
<td>+0.9%</td>
<td>-9.5%</td>
<td>-31.4%</td>
<td>-7.3%</td>
<td></td>
</tr>
<tr>
<td>Oligopoly within format</td>
<td>4.4pdm</td>
<td>-4.5pdm</td>
<td>-253.4m</td>
<td>-9,056min</td>
<td>+1.12%</td>
</tr>
<tr>
<td></td>
<td>+0.8%</td>
<td>-9.0%</td>
<td>-31.3%</td>
<td>-5.6%</td>
<td></td>
</tr>
<tr>
<td>Perfect substitutes</td>
<td>4.9pdm</td>
<td>-8.3pdm</td>
<td>-314.7m</td>
<td>-16,648min</td>
<td>+2.57%</td>
</tr>
<tr>
<td></td>
<td>+0.9%</td>
<td>-10.3%</td>
<td>-32.7%</td>
<td>-9.0%</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.12: Robustness of counterfactuals

The estimated slope tends to be higher. Despite the fact that there are statistical differences between the different models, the main qualitative assertion, that stations have more power in smaller markets, still holds. In order to assess the economic implication of those differences, I recomputed the estimated profit margin under different models. It turns out that the model with format oligopoly predicts on average a 2.4% higher profit margins than the baseline model. Conversely the model with perfect substitutes predicts 2.1% lower profit margin.

To draw final conclusions about the strength of the assumption about weights, I recomputed the main counterfactual using the alternative models. The results are presented in Table 2.12. The baseline again lies between the new counterfactuals. There is no qualitative change in the results. Moreover the percentage changes in consumer and advertiser surplus are almost the same. Consequently, I conclude that the results of the paper are not sensitive to changes in the assumption about substitution between formats.

2.9 Conclusion

In this paper I analyze mergers in two-sided markets on the example of the 1996-2006 consolidation wave in U.S. radio industry. The goal of this study is to describe and quantify how mergers in the two-sided market differ from a differentiated product
CHAPTER 2. MERGERS IN TWO-SIDED MARKETS

oligopoly setting. I make two main contributions. First, I recognize the fact two-sided markets consist of two types of consumers, who may be affected by the merger in different ways. For example, if extra market power causes the radio station to increase advertising, it will benefit consumers but hurt advertisers. Second, I disaggregate the impact of a merger on consumers into changes in the variety of available products and changes in supplied quantity of ads.

Radio is an important medium in the U.S., reaching about 94% of Americans twelve years old or older each week. Moreover, the average consumer listens to about 20h of radio per week and between 6am and 6pm more people use radio than TV or print media. In 1996 the Telecommunication Act deregulated the industry by raising local ownership caps. This deregulation caused a massive merger wave, that reshaped the ownership structure, by moving from family based ownership into more corporate structures. I estimate that this consolidation raised consumer surplus by 1%, but lowered advertiser surplus by $300m. I find that the mergers created extra variety that increased listener welfare by 1.3%. On the other hand they softened competition and decreased advertiser welfare by $147m per year. Subsequent ad quantity adjustments led to a 0.3% decrease in listener welfare (with the variety effect it totals to the 1% increase) and an additional $153m decrease in advertiser welfare (with the variety effect it totals $300m).

\[^5\text{Source: A.Richter (2006)}\]
Chapter 3

Estimation of cost synergies from mergers without cost data: Application to U.S. radio

3.1 Preface

This chapter develops a new way to estimate cost synergies from mergers without using actual data on cost. The estimator uses a structural model in which companies play a dynamic game with endogenous mergers and product repositioning decisions. Such a formulation has several benefits over the widespread static merger analysis. In particular, it corrects for sample selection of more profitable mergers and captures follow-up mergers and post-merger product repositioning.

The framework is applied to estimate cost efficiencies after the deregulation of U.S. radio in 1996. The procedure uses the data on radio station characteristics and numerous acquisitions, without explicit need for cost data. It turns out that between 1996 and 2006 additional ownership concentration generated $2.5b per-year cost savings, which is about 10% of total industry revenue.
CHAPTER 3. COST SYNERGIES FROM MERGERS

3.2 Introduction

The extent to which a potential merger generates cost efficiencies is often mentioned by managers as a major motivation to merge. Moreover, potential fixed cost savings generated by a merger are recognized by the Horizontal Merger Guidelines as a factor that can provide consumers with direct price-related as well as non-price-related benefits. Thus, for antitrust purposes one should evaluate cost savings in addition to measuring the decrease in competition. However, this approach is rarely used in practice, because in most cases reliable cost data are unavailable. This paper provides a solution to this problem, by proposing a method to estimate cost synergies without using any data on cost. This method requires only panel data on the ownership structure, product characteristics, and prices and quantities, information that in most cases is easily accessible.

Evaluating the underlying causes of ownership consolidation requires a dynamic model in which mergers are endogenous. However, most past empirical work analyzed mergers in a static framework and treats market structure as given. Papers by Nevo (2000), Pinkse and Slade (2004), Ivaldi and Verboven (2005) exogenously impose changes in market structure on a static equilibrium model and calculate counterfactual changes in prices and welfare. These models are very useful in addressing the short run impacts of mergers but do not account for changes in market structure that might happen as a result of a merger. Benkard, Bodoh-Creed, and Lazarev (2008) evaluate the longer run effects of a merger on market structure, but still treat it as an exogenous one-time event. Neither of these approaches allows for estimating the supply side determinants of mergers, such as cost synergies. Furthermore, the assumption that mergers are exogenous may create a selection bias that results in overestimating the cost synergies (we might pick up other unobserved components correlated with the propensity to merge). Furthermore, recent models assume away follow-up mergers and post-merger repositioning of products.

To address these issues, I propose a dynamic model in the spirit of Gowrisankaran (1999) in which mergers and product positioning are endogenous and are assumed to happen sequentially. Such an approach enables me to estimate the cost efficiencies
of consolidation without any data on cost. It also eliminates the shortcomings mentioned earlier, because it incorporates the dynamic processes directly into the model. Moreover, endogenizing mergers allows for correction of sample selection by using a procedure in the spirit of Heckman (1979), adjusted for a dynamic game environment.

The model is subsequently applied to analyze ownership consolidation in the U.S. radio industry. The Telecommunications Act of 1996 increased local-market radio station ownership caps, triggering an unprecedented merger wave that had the effect of eliminating many small and independent radio owners. From 1996 to 2006, the average Herfindahl-Hirschman Index (HHI) in local radio markets grew from 0.18 to 0.26, the average number of owners in the market dropped from 16.6 to 12.4, and the average number of stations owned grew from 1.6 to 2.3. Such dramatic changes to the market structure have raised concerns about anti-competitive aspects of the deregulation (Leeper (1999), Drushel (1998), Klein (1997)). After estimating the model using the method of Bajari, Benkard, and Levin (2004), I find that the main incentives to merge in radio come from the cost side. Total cost side savings amount to $2.5b per year, constituting about 10% of total industry revenue. Such cost synergies are an order of magnitude higher than the anti-competitive effects of these mergers identified by Jeziorski (2010). Moreover, the fact that consolidation leads to substantial cost side synergies leads me to conclude that the Telecom Act made radio advertising more competitive against other media, such as TV or the Internet.

To my knowledge, Gowrisankaran (1999) is the only applied paper that uses a dynamic framework to endogenize mergers. His analysis argued that merger dynamics are very important. The main drawback of his analysis is that it was never fit to real data. This was due in part to the complexity of his model and in part to the lack of a good dataset. To solve the complexity problem, I utilize the latest developments in the dynamic-games literature. These developments enable us to estimate very complicated models without explicitly solving them (Bajari, Benkard, and Levin (2004)). This paper also contributes to empirical literature on demand and cost curve estimation (this started with Rosse (1970) and Rosse (1967)), by accounting explicitly for the demand side incentives to merge. On the technical side,
my model shares some similarities with Sweeting (2007). I concentrate on questions about incentives to merge and the impact of consolidation on welfare, while Sweeting focuses mainly on estimates of the format switching cost. My analysis also extends his model by adding a model of ad quantity choices and endogenous mergers. Another paper on a similar topic is O’Gorman and Smith (2008). They use a static oligopoly model to estimate the cost curve in radio. They find that the fixed cost savings when owning two stations is bounded between between 20% and 50% of per-station costs (I estimate this number to be 20%). I supplement their estimates by accounting for selection bias, follow-up mergers and post-merger repositioning as outlined above.

This chapter is organized as follows. Section 2 contains a flexible, structural merger model that can applied to many industries. The estimation procedure is discussed in Section 3. Section 4 describes the application of the framework to analyze the merger wave in the U.S. radio industry. Section 5 concludes the paper.

3.3 Merger and repositioning framework

This section presents the dynamic oligopoly model of an industry with differentiated products in the spirit of Ericson and Pakes (1995). The industry is modeled as a dynamic game and the players are companies holding portfolios of different products (brands). The modeling effort emphasizes the actions of companies changing the portfolio of owned products, specifically rebranding and acquisitions. The model is general enough to encompass a number of different industries and types of competition, by allowing for a large range of different single-period profit functions and cost structures.

3.3.1 Industry basics

The industry is composed of $M$ different markets that operate in discrete time over an infinite horizon. The payoff relevant market characteristics at time $t$ are fully characterized by a set of covariates $d^{mt} \in \mathcal{D}$ that include demand shifters. In each market $m$, there are up to $K_m$ operating firms and up to $J_m$ active products. Let $o_j \in$
$K_m$ be the owner of the product $j$. I assume that each product $j \in J_m$ is characterized by a triple $s^t_j = (f^t_j, \xi^t_j, o^t_j)$. In particular, $f^t_j \in F$ is a discrete characteristic, and $\xi^t_j \in \Xi$ is a continuous characteristic of the product. The state of the industry at the beginning of each period is therefore a duple $(s^t, d^t) \in S \times D$.

To simplify the further exposition define $O^t_k$ to be the number of products owned by the firm $k$, and $O^t_{-k}$ to be the number of products owned by its competitors.

### 3.3.2 Players’ actions

Firms can undertake two types of actions: product acquisitions and product repositioning. I assume that acquisitions take place first and the results are common knowledge before the firms commence with repositioning.

In general, the product acquisition process can be very complicated. Firms can acquire any subset of products owned by competitors, and multiple firms can bid to acquire the same product. Therefore, the most general model of this process is likely to be intractable both analytically and numerically. Additionally, the model of mergers without additional structure is likely to generate multiple equilibria, which will significantly complicate its estimation. To solve these problems, I follow Gowrisankaran (1999) and I assume that the station acquisition process is sequential. Owners move in a sequence specified by a function $A : s^t \mapsto i$, where $i$ is a permutation of the active owners’ index $\{1, \ldots, K\}$. In addition, for notational purposes, I set $i(K + 1) = K + 1$.

Let $\omega^t_{i(k)}$ be the state of the industry observed by the k-th mover in the merger process, before making acquisition decisions. $\omega^t_{i(1)}$ is set to be equal to $s^t$. Additionally, every player observes a set of acquisition prices for all stations owned by competitors

$$P^t_k = \{\phi^t_{kj} : o^t_j \neq k\}$$

These prices are the outcomes of a bargaining process that is only a function of the current observable state $\omega^t_{i(k)}$. This assumption holds if $\omega^t_{i(k)}$ is the only payoff relevant variable for both the acquirer and the acquiree and the prices are determined by a Nash Bargaining Solution.

In addition to prices, the potential buyer observes a set of additive payoff/cost
shocks from acquiring any competitor owned product \( \phi_k^t = \{ \phi_{kj}^t : o_j^t \neq k \} \) that is his private information. A player’s \( i(k) \) action involves specifying which subset of stations are to be acquired. I restrict attention to Markov strategies, so the acquisition policy is a mapping

\[ a_k : (\omega_{i(k)}^t, \phi_k^t, P_k^t, d^t) \mapsto \{0, 1\}^{O^t} \]

After the decisions are made, a new ownership \( \omega_{i(k+1)}^t \) is determined, and it becomes common knowledge. Player \( a(k+1) \) proceeds with acquisitions, or if there are no move active players, the game moves to product repositioning.

A product repositioning involves decisions about changing discrete characteristics \( f_j^t \) of owned products, in exchange for paying a switching cost \( C(f_j^t, f_j^{t+1}) \). It is, similarly to acquisitions, a sequential process, and it is assumed that firms proceed according to the same sequence \( i(k) \).

The first mover \( i(1) \) in the repositioning process conditions his decision on the state of the industry after the acquisitions, i.e., the observable state \( \hat{\omega}_{i(1)}^t \) is equal to \( \omega_{i(K+1)}^t \). In the same way the k-th mover \( i(k) \) observes the repositionings done by all the previous movers. This information is summarized in \( \hat{\omega}_{i(k)}^t \). In addition to observing the state \( \hat{\omega}_{i(k)}^t \), the k-th mover observes payoff/cost shocks for all the products of any potential type \( \psi_k^t = \{ \psi_{kjf}^t : o_j^t = k, 1 \geq f \geq F \} \). The product repositioning policy is a Markov strategy given by the mapping

\[ b_k : (\hat{\omega}_{i(k)}^t, \psi_k^t, d^t) \mapsto F^{O_k^t} \]

When the choices of player \( i(k) \) are made a new industry state \( \hat{\omega}_{i(k+1)}^t \) becomes a common knowledge.

After repositioning the new industry state \( (s^{t+1}, d^{t+1}) \) is determined. \( s^{t+1} \) is constructed by combining \( \hat{\omega}_{i(K+1)}^t \) with the values of a new continuous product characteristic \( \xi^{t+1} \). The following assumptions restrict the dynamics of \( \xi \).

**Assumption 3.3.1.** \( \xi_{jt} \) evolves as an exogenous Markov process, for example

\[ \xi_{jt} = \rho \xi_{jt-1} + \zeta_t \]  \hspace{1cm} (3.1)
where $\zeta_t$ is a mean zero IID random variable.

Moreover, market covariates are also assumed to be exogenous and Markov

**Assumption 3.3.2.** $d^t$ evolves as an exogenous Markov process.

These assumptions are made for simplicity of estimation. They could be potentially relaxed if more data is available. For example, if $\xi$ is a product quality, one could assume that it is also a dynamic choice variable and estimate it directly from the observed investment.

When the new industry state is $(s^{t+1}, d^{t+1})$ realized firms then play a static competition game that yields profits given by $\bar{\pi}_k(s^{t+1}, d^t)$.

### 3.3.3 Payoffs and equilibrium

Given the realizations of $(s^t, s^{t+1}, P^t, \psi^t, \phi^t, d^t)$ the per-period payoff for player $k$ is given by the equation

$$
\pi_k(s^t, s^{t+1}, P^t, \psi^t, \phi^t, d^t) = \bar{\pi}_k(s^{t+1}, d^t) - F(s^t_k) + \sum_{j: o^t_j \neq k, o^{t+1}_{j} = k} (\phi^t_{kj} - P^t_{kj}) + \\
\sum_{j: o^t_j = k, o^{t+1}_{j} \neq k} P^t_{o^t_j o^{t+1}_j} + \sum_{j: o^{t+1}_j = k} \left[ \psi^t_{kj} f_{jt}^{t+1} - I(f_{jt}^{t+1} \neq f^t_{j}) C(f^t_{j}, f_{jt}^{t+1}) \right] \quad (3.2)
$$

where $F(s^t_k)$ is the fixed cost of owning portfolio $s^t_k$, and $\bar{\pi}_k$ is a one-shot profit from the portfolio.

Let $g = (a_1, \ldots, a_K, b_1, \ldots, b_K)$ be a Markov strategy profile. It can be shown that this profile and an initial condition $(s, d)$ determine the unique, controlled Markov process over states, acquisition prices $P$, payoff shocks $\psi$ and $\phi$, and market covariates $d$

$$
\mathcal{P}(g, s, d) \in \Delta(S \times P \times \Psi \times \Phi \times D \times T)
$$

where $T$ is a time horizon, and $\Delta$ is a set of probability measures. $\mathcal{P}$ is therefore a discrete time stochastic process on $S \times P \times \Psi \times \Phi \times D$. This process is also supplied with a filtration, such that the strategy profile $g$ is measurable.
Each owner is maximizing the expected discounted sum of profits taking the strategies of opponents $g_{-k}$ as given. The value function for player $k$ is defined as

$$V_k(s, d|g_k, g_{-k}) = E_{P(g,s,d)} \sum_{t=0}^{\infty} \beta^t \pi_k(s^t, s^{t+1}, P^t, \psi^t, \phi^t, d^t)$$

(3.3)

It is assumed that the markets are in a Markov Perfect Equilibrium, i.e., firms choose strategy profile $g^*$, such that for all $k$

$$V_k(s, d|g_k^*, g_{-k}^*) \geq V_k(s, d|g_k, g_{-k}^*) \forall g_k.$$  

(3.4)

For simplicity, I restrict my attention to symmetric equilibria. The next section describes the estimation procedure.

### 3.4 Estimation

Consider parameterizations of the fixed cost $F(s_k^t|\theta_F)$ and the switching cost $C(f_j^t, f_j^{t+1}|\theta_C)$. This section outlines a procedure, based on Bajari, Benkard, and Levin (2004), to obtain consistent estimators of $\theta_F$ and $\theta_C$ without using direct data on cost.

The procedure has two stages. The first stage infers equilibrium behavior from the data on one or a set of similar industries. The second stage estimates the cost parameters for a particular industry by imposing the dynamic game equilibrium inequalities 3.4. The following subsection describes the data needed for this procedure to work.

### 3.4.1 Data

Consider an industry, or a set of similar industries, operating in $M$ markets over the discrete time span $T$. Data is given by the set $X = \{x^{tm}: 1 \leq m \leq M, 1 \leq t \leq T\}$. Each point in the data $x^{tm}$ describes the state of the industry at the beginning of the period $s^{tm} = (f^{tm}, \xi^{tm}, \sigma^{tm})$, market covariates/demand shifters $d^{tm}$, and a set of transaction prices $P^{mt}$. The data does not have to contain any direct information on
the cost. This is convenient since most of the data on cost suffers from accounting issues. Therefore direct cost estimates from the data might be unreliable.

To facilitate the inference process a standard assumption about the data generating process is made: that it is generated by a single MPE strategy profile $g^*$. Crucially, the dataset needs to contain a reasonable amount of within market acquisitions and repositioning to allows it to identify equilibrium strategies. Sometimes it is possible to obtain such datasets within one industry (see U.S. radio in the application), however for most industries such datasets are unavailable. In this case, it is possible to pool similar industries to construct one dataset. To make this work one needs a slightly stronger assumption that equilibrium behavior is the same across the pooled industries.

The transaction prices are helpful but not necessary to identify the cost parameters. Estimation is possible without them but it requires more assumptions about the bargaining process during the acquisition, as well as much more computing power. The extra steps needed to proceed without the prices are mentioned in Appendix B.1.

In order to simplify the exposition all state variables are assumed to be observed. However, the procedure also applies to problems in which some payoff relevant information is unobserved to the econometrician. In many cases one can infer the unobserved state variable from a static estimation of the one-shot profit function $\bar{\pi}$.

One example of such a case is Berry, Levinsohn, and Pakes (1995) estimator, which uses differences of static market shares to identify unobserved product quality. Moreover, there are numerous ways to proceed in case one cannot directly infer all the latent state variables. For example, one could supply the procedure from this chapter with an EM algorithm proposed by Arcidiacono and Miller (2010).

### 3.4.2 Policy estimation

For any strategy profile $g = (a_1, \ldots, a_K, b_1, \ldots, b_K)$ let $\text{Prob}_k^M(a_k|\omega_k, d_k)$, and $\text{Prob}_k^R(b_k|\tilde{\omega}_k, d_k)$, be the probabilities of taking acquisition and repositioning actions. The former is a probability measure on $\{0, 1\}^{O-k}$, and the
latter on \{1,\ldots,F\}^{O_k}. They are constructed by integrating out unobservable payoff shocks \(\phi\) and \(\psi\). The goal of this subsection is to provide a procedure that allows us to obtain the estimates of these probability measures. This procedure leverages on the sequentiality assumptions made in the previous section.

The first step of the procedure is constructing an auxiliary dataset using a sequential structure of the acquisition and repositioning process. For each \(t\), the predefined sequence of player moves \(i = I(s_t)\) specifies a mapping

\[
(s_t, s_{t+1}) \mapsto (\omega_i(1), \ldots, \omega_i(K), \tilde{\omega}_i(1), \ldots \tilde{\omega}_i(K))
\]

This mapping is used to construct 3 sets. The first set describes the acquisition dynamics

\[
Y_1 = \{ (\omega_k^{tm}, d_k^{tm}, a_k^{tm}) : 1 \leq k \leq K, 1 \leq m \leq M, 1 \leq t \leq T \}
\]

where \(a_k^{tm}\) is a vector of zeros and ones that indicates acquisition decisions for player \(k\). The second set describes acquisition prices

\[
Y_2 = \{ (\omega_k^{tm}, d_k^{tm}, P_k^{tm}) : 1 \leq k \leq K, 1 \leq m \leq M, 1 \leq t \leq T \}
\]

where \(P_k^{tm}\) is a vector of prices for all acquisitions of player \(k\). The last set describes the repositioning

\[
Y_3 = \{ (\tilde{\omega}_k^{tm}, d_k^{tm}, F_k^{mt}) : 1 \leq k \leq K, 1 \leq m \leq M, 1 \leq t \leq T \}
\]

where \(F_k^{mt}\) is a vector of chosen characteristics for products owned by firm \(k\).

Set \(Y_1\) is used to estimate the acquisition probability distribution \(\text{Prob}_k^M\) as a function of \((\omega, d)\). In a perfect world, one would like to employ a form of non-parametric multi-dimensional discrete choice estimator. However, in practice, the researcher is likely to face two problems: the large dimensionality of covariates \((\omega, d)\) and the large dimensionality of the \(\text{Prob}_k^M\) support (due to a big number of active products/companies that can be acquired).
The solution to the first problem is to employ a flexible parametric form

\[ \text{Prob}_k^M (a_k | \omega_k, d_k, \theta_M) \]

that exhausts most of the information in the data. The asymptotics of such an estimator are similar to the non-parametric estimators in which the dimensionality of pseudo-parameters \( \theta_M \) grow as the dataset becomes large.

The second problem is more severe and in most cases cannot be solved without additional assumptions. The following examples suggest different possible approaches.

**Example 3.4.1** (One acquisition per period). *If the acquisitions in the data tend to be rare, one could potentially assume that only one acquisition per owner is allowed each period. This reduces the decision space to only one dimension and enables direct application of any discrete choice model (for example logit or probit) on the data set \( Y_1 \).*

The second example suggests how to deal with multiple acquisitions

**Example 3.4.2** (Independent acquisitions). *In the case where the acquisition decisions are uncorrelated conditional on \( \omega_k \) and \( d_k \) one could employ a discrete choice regression directly on \( Y_1 \), fixing \( \omega_{tm}^k \) for all decisions in \( a_{tm}^k \).*

The next solution makes more assumptions about the structure of the acquisition decision making within the firm.

**Example 3.4.3** (Sequential acquisitions). *Suppose that the acquisition decisions are made in a sequence, i.e., after observing \( \psi_j \) for a particular product, the firm decides about its acquisition without looking at the payoff shocks \( \psi \) for other stations. In this case one could further expand dataset \( Y_1 \) to incorporate the sequence of decisions within the firm. Because of the additive structure of payoffs and the fact that \( \psi_j \) are IID, one could consistently estimate \( \text{Prob}_k^M \) by using a discrete choice estimator on the extended dataset.*

If one were to observe the acquisition prices one could estimate the pricing function \( P(\omega_k^{st}) \) directly from the dataset \( Y_2 \). This could be achieved by employing the flexible
CHAPTER 3. COST SYNERGIES FROM MERGERS

parametric interpolation\(^2\).

When estimating the repositioning probabilities \(\text{Prob}_k^R\), one faces similar problems, but additionally one has to deal with multinomial vs. binomial choice. The three examples of solutions to that problem presented previously also apply here.

Additionally, one could endogenize the continuous characteristic \(\xi\) and estimate it as a function of the state space using the methods presented in Bajari, Benkard, and Levin (2004). Depending on the interpretation of \(\xi\), this might involve an additional model. In this paper however, \(\xi^t\) as well as \(d^t\) are treated as exogenous and Markov. The transition in this case can be estimated as a flexible parametric auto-regressive process.

In the next subsection I describe a second stage of the cost function estimator that uses the estimators of equilibrium policy and the transition of \(\xi\) and \(d^t\) obtained in the first step above.

### 3.4.3 Minimum distance estimator

For the second stage the parameters of the fixed cost \(\theta_F\) and repositioning cost \(\theta_R\) are estimated using a minimum distance estimator. The estimator is constructed using the MPE inequalities (3.4). The remainder of this section describes how I obtain estimates of the value functions in those inequalities.

The value function \(V_k\) (defined on the equation (3.3)) can be separated into four parts.

\[
V^t_k = A^t_k + \theta_\phi B^t_k + \theta_\psi C^t_k + D^t_k
\]

where

\[
A^t_k = E \sum_{r=t}^{\infty} \beta^{r-t} \pi_k(s^t, d^t) + \sum_{j: o_r^j=k, o_r^{j+1} \neq k} P_{o_r^j} - \sum_{j: o_r^j \neq k, o_r^{j+1} = k} P_{o_r^j}
\]

\(^2\)Sometimes the dataset on prices is sparse, i.e., one does not observe prices for every deal. In this case more simplifying assumptions about the pricing process are needed.
is the expected stream of advertising revenues,

\[ B^t_k = E \sum_{r=t}^{\infty} \beta^{r-t} \sum_{j: \sigma^*_j \neq k, \sigma^*_j+1 = k} \phi^r_{kj} \]

is the expected stream of acquisition payoff/cost shocks,

\[ C^t_k = E \sum_{r=t}^{\infty} \beta^{r-t} \sum_{j: \sigma^*_j+1 = k} \psi^r_{kj f^*_j f^*_j+1} \]

is the expected stream of repositioning payoff/cost shocks, and

\[ D^t_k = E \sum_{r=t}^{\infty} \beta^{r-t} \left[ F(s^*_k | \theta_F) + \sum_{j: \sigma^*_j+1 = k} 1(f^*_j+1 \neq f^*_j) C(f^*_j, f^*_j+1 | \theta_C) \right] \]

is the expected stream of fixed costs and repositioning costs. The extra parameters \( \theta_\phi \) and \( \theta_\psi \) are needed because the first stage estimation requires normalization of the variances of \( \phi \) and \( \psi \).

Accounting for \( B^t_k \) in the simulation of profits from a merger takes care of selection on unobservables, as opposed to the usual static approach to mergers. Given the merger decision \( a^m_{jk} \), the contribution of unobserved profits is \( \theta_\phi E[\phi^m_{jk} | a^m_{jk}] \). Because a company observes the payoff shock before making an acquisition, the mergers that occur are selected for high value of \( \phi^m_{jk} \). When \( \phi \) has zero mean, it is the case that \( E[\phi^m_{jk} | a^m_{jk} = 1] > 0 \). Failing to account for that (i.e. assuming that \( E[\phi^m_{jk} | a^m_{jk} = 1] = E[\phi^m_{jk}] = 0 \)) would cause underestimation of profits from mergers and overestimation of fixed cost synergies\(^3\). The same point can be made about the selection on unobservables when repositioning products and inclusion of \( C^t_k \).

Note that only the last part of \( D^t_k \) depends on the parameters of interest \( \theta_F \) and \( \theta_C \) and the value function is linear \( \theta_\phi \) and \( \theta_\psi \). Therefore, to compute the value function

\(^3\)When using any of the dynamic likelihood estimators proposed in the previous subsection and assuming that \( \phi \) is a difference of two independent Type I extreme value random variables, \( E[\phi | a = 1] \) can be reduced to \( -\log(p) - \frac{1-p}{p} \log(1-p) \), where \( p \) is a probability of acquisition.
CHAPTER 3. COST SYNERGIES FROM MERGERS

for different parameter values one does not need to re-simulate the industry path \((s^t, d^t)\); moreover, one does not need to recompute any of \(A^t_k, B^t_k, C^t_k\). This saves a large amount of processing power and makes the estimator feasible using today’s computers.

Following the inequality (3.4), let \(V^t_k\) be an equilibrium value function for player \(k\), \(V_k(\cdot|g^*_k, g^{*\_k})\). Additionally, define a suboptimal value function \(\tilde{V}^t_k\) to be \(V_k(\cdot|g_k, g^*_k)\) for some off-equilibrium strategy \(g_k\). In equilibrium, I know that \(\max\{\tilde{V}^t_k - V^t_k, 0\} = 0\) for the true values of \(\theta_M\) and \(\theta_R\). Thus, I define a minimum distance estimator

\[
(\hat{\theta}_M, \hat{\theta}_R) = \arg\min \frac{1}{K \times T \times M} \sum_{k,t,m} \frac{1}{A^t_k} \| \max\{\tilde{V}^t_k - V^t_k, 0\} \|
\]

According to the results in Bajari, Benkard, and Levin (2004) this estimator is consistent and asymptotically normal. This finishes the description of the estimator. An example of its application is contained in the next section.

3.5 Application

In this section, I describe how to use above framework to estimate merger synergies from ownership consolidation in the U.S. radio industry. In the next subsection I give a brief review of the industry. The second subsection presents the tailored version of the estimation algorithm. The last subsection presents and discusses the results.

3.5.1 Industry and data description

Radio is an important medium in the U.S., reaching about 94% of Americans twelve years old or older each week. Moreover, the average consumer listens to about 20 hours of radio per week and between 6am and 6pm more people use radio than TV or print media.\(^5\) There are about 13,000 commercial radio stations that broadcast in about 350 local markets nationwide. Before 1996, this industry had ownership

\(^4\)In most cases \(A^t_k\) is the hardest to compute because computing \(\bar{\pi}\) may involve solving a one-shot Nash equilibrium price or a quantity setting game.

limitations both nationally and locally, preventing big corporations from entering the market and thereby sustaining a large degree of family based ownership. This situation changed with the Telecom Act of 1996 which, among other things, raised the ownership caps in the local markets (see Table 3.1).

This triggered an unprecedented merger and product repositioning wave that completely reshaped the industry. Figure 3.1 contains the average percentage of stations that switched owners and that switched formats. Between 1996 and 2000 more than 10% of stations switched owners annually. After 2000 the number dropped to less than 4%. Greater ownership concentration in the 1996-2000 period was also associated with more format switching. The percentage of stations that switched formats peaked in 1998 and 2001 at 13%. In effect, the Herfindahl-Hirschman Index (HHI) in the listenership market grew from 0.18 in 1996 to about 0.3 in 2006.

The impact of this consolidation on consumer surplus has been studied before using a static demand and supply approach. For example Jeziorski (2010) (Chapter 2 of this thesis), finds that consolidation of ownership in this industry was harmful to advertisers, causing $300m loss in advertiser surplus, but beneficial to listeners, raising the welfare by 1%.

In order to analyze the supply side effects of this consolidation, I compiled a dataset on stations in the 88 markets studied by Jeziorski (2010). The data contains ownership for each station $o_j$, and station format $f_j$. It uses the estimates of station quality $\xi_j$, contained in Jeziorski (2010). I also observe each acquisition made in this market and the average acquisition price.

---

### Table 3.1: Change in the local ownership caps introduced by the 1996 Telecom Act.

<table>
<thead>
<tr>
<th># of active stations</th>
<th>Old ownership cap</th>
<th>New cap</th>
</tr>
</thead>
<tbody>
<tr>
<td>45+</td>
<td>4</td>
<td>8</td>
</tr>
<tr>
<td>30-44</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>15-29</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>0-14</td>
<td>3</td>
<td>5</td>
</tr>
</tbody>
</table>

---

6Data is constructed using the software provided by BIA Financial Network Inc. and Media Market Guides by SQAD
3.5.2 Static profits

The static profit function is taken directly from Jeziorski (2010). Radio station owners draw their revenue from selling advertising and each advertising slot is priced on a per listener basis. The total profit of the owner $k$ is equal to

$$\bar{\pi}_k(s, d) = \sum_{j: \alpha_j = k} r_j(q^*, s, d)p_j(q^*, s, d)q_j^*$$

where $q^*$ are the equilibrium advertising quantities chosen in the static oligopoly game, $r_j$ is the number of listeners and $p_j$ is the price per listener. In this paper, I treat the estimates of this profit function as given; however, I do correct the standard errors of the dynamic estimates by accounting for the noise introduced by estimating profit function.

The only difference between the baseline model in Jeziorski (2010) and the profit function used in this chapter is that the marginal cost of production is set to zero and format substitution matrix $\Omega$ is assumed to be diagonal. I made these assumptions
CHAPTER 3. COST SYNERGIES FROM MERGERS

for computational reasons.

3.5.3 Estimation details

The estimation is a direct application of the framework described in subsection 3.4. The model endogenizes acquisition decisions and format switching decisions. The dynamics in an unobserved radio station quality $\xi$ is assumed to be exogenous.

The first piece of the model that needs to be specified is the function $I(s^t, d^t)$, that prescribes the sequence of moves firms make in the merger and repositioning process. Following Gowrisankaran (1999), I assume that firms with the biggest total market shares move first. This is motivated by the fact that the bigger players in the market might have a first-mover advantage over smaller players. The acquisition price is assumed to be constant within market and equal to the observed mean acquisition price.

To estimate the merger probability I use the method outlined in the Example 3.4.3. Each owner considers, one at a time, stations to acquire, starting from the one with the highest quality measure $\xi_j$, and moving down according to $\xi_j$. A flow chart of the merger process is presented in the Appendix B.2. Such structure enables expanding the data structure on acquisitions within the firm

$$(\omega^t_k, a^t_k) \mapsto (\omega^t_{jk}, a^t_{jk})_{j=1}^{O^t_k}$$

where $O^t_k$ is the number of stations owned by competitors. If we assume that $\psi$ is a difference of two extreme value distributions and is also revealed in a sequence, one can consistently estimate a probability of merger $\text{Prob}^M_k$, by running a regular logit regression on this extended dataset.

The covariates in the logit regression should reflect the information about the state space contained in the data. In a perfect world one would use a very flexible index function of the state space variables. However, because of high dimensionality of the state space, such an approach requires too many degrees of freedom, and quickly

$^7$Choice of $\xi_j$ as an ordering characteristic is motivated by the fact that it is a vertical measure of profitability.
exhausts all the information available in the data. To overcome this problem, I use a linear index function of several statistics about the state space computed from the data\(^8\). The full set of covariates can be found in Table B.1 in Appendix B.3.

A similar strategy can be employed to estimate the format switching process. The flow chart describing this process is contained in Appendix B.2. Assuming that firms switch formats sequentially dictates the following dataset expansion

\[
(\omega^t_k, a^t_k) \mapsto (\omega^{t}_{jk}, a^{t}_{jk})_{j=1}^{O_{t-k}}
\]

Using this auxiliary dataset one can apply a multinomial logit model to estimate the format switching probabilities \(\text{Prob}_k^R\). The restriction on the index function also applies in this case, so I use only a limited set of covariates (given in Table B.2 in Appendix B.3).

In the second stage of the estimation, I parametrize the fixed cost function

\[
F(s_{tm}^m) = \theta_1 \times \text{POP}_m \times n_{kt} \theta_2 
\]

where \(\text{POP}_m\) is a population of the market \(m\) and \(n_{kt}\) is the number of stations owned by player \(k\) at time \(t\). Parameter \(\theta_{C2}\) dictates the amount of cost synergies from owning multiple stations. I also assume a constant format switching cost that is proportional to the population. Those assumptions are motivated by the fact that Jeziorski (2010) finds that most of the variation in marginal cost of radio operations between can be explained by the variation in total population.

In the second stage, I simulate the value function only for the owner with the biggest market share at each data point \((s_{tm}^m, d_{tm}^m)\). These simulations are done according to the Algorithms 2 and 3. The suboptimal value function \(\tilde{V}_k\) is obtained by multiplying the merger and format switching probability by a uniform \([.95, 1.05]\) random variable. When choosing the size of the perturbations one faces a bias and variance trade-off. When the size is too small the estimator start picking up the noise from the simulations instead of the sub-optimality of the strategy, decreasing

\(^8\)a similar approach can be found in Sweeting (2007), Ryan (2005), Ryan and Tucker (2006), and Ellickson and Arie (2005).
the efficiency of the estimator. When the size is chosen to be too big, the bounds of
the estimator become very large creating potential bias. The chosen perturbation is
a compromise between those two factors.

3.5.4 Results

This subsection describes the results of the estimation. The exposition is divided into
two parts. First, I present the policy function estimates. Then, I report the main
results on fixed cost and switching cost synergies.

First stage: Policy function

Tables B.3 and B.4 report coefficients from a purchase strategy probit approxima-
tion. They reveal that owners with larger market shares are more likely to purchase
new stations and are less likely to sell. Also, there are synergies when purchasing
multiple stations. The coefficient on the first purchase dummy PUR0 is negative while
coefficients on dummies for multiple purchases are positive. This indicates that it
is easier to negotiate the purchase of many stations, or even an entire company at
once, than a single station. The number of owned stations in the format (the FORMAT
variable in the table) has a negative influence on purchase decisions. This is evidence
for diversification. The coefficient of station quality is positive which suggests that
stations with higher quality are purchased more often.

Table B.5 presents the influence on future format of the following covariates:
change of ownership dummy, AM/FM status, and previous format. The negative
coefficient of a Spanish format in the first row of the table suggests that when a
station is purchased it is less likely to switch to Spanish format. On the other hand,
the positive coefficient of AC tells us that change in ownership is correlated with
switching to the Adult Contemporary format. The second column of the table shows
that FM stations are likely be of Rock or CHR format, and not so likely to be of
News/Talk format. The remaining rows of the table describe the Markov dynamics
of formats. The diagonal cells have much higher numbers than the off-diagonal ones,
which reflects the fact that staying in the current format is much more probable than
switching.

Table B.6 presents the relationship between the current demographic composition of the market format switching decisions. In addition, Table B.7 contains similar information concerning the dynamics of the demographics (the difference between two consecutive periods) and format switching. One can observe many patterns that suggest firms respond to the current state of population demographics as well as to the dynamics of population demographics. For example, a larger current population and growth of the Hispanic population is related to the stations switching to a Hispanic format. One can observe a similar pattern for Blacks and the Urban format, as well as for older people and the News/Talk format. Those patterns largely reflect correlations between tastes for formats and demographics described in Jeziorski (2010).

Second stage: Fixed and switching cost

The estimated parameters of the fixed cost equation (3.5) are as follows: \( \hat{\theta}_{C_1} = 0.69 \) and \( \hat{\theta}_{C_2} = 0.59 \). Table 3.2 interprets the economic significance of these parameters in terms the amount of saved fixed costs per year if two stations are commonly owned compared to being separate companies. Since the amount of cost synergies depends on the market population, only three representative markets are presented. Los Angeles is the biggest market in the sample and the cost savings in that market amount to about $4.4m per-year (roughly 10% of the revenue of a big station). Knoxville is representative of medium markets and has about $0.23m of such cost savings, and Bismark, a small market, has about $34k of savings. Table 3.3 presents total cost savings from all mergers after the Telecom Act was passed. It turns out that the merger activity lowered the fixed cost of providing radio programming by almost $2.5b, amounting to almost 10% of the total revenue of the industry. Compared to that, the impact on advertiser surplus identified in Jeziorski (2010) is very small. This leads me to conclude that the deregulation of 1996 provided substantial operational efficiencies that outweigh negative impacts on advertiser welfare.

The last set of estimates concern the product repositioning costs. The estimate of the cost parameter \( \hat{\theta}_C \) is 2.1. The repositioning cost for each market is the population of that market multiplied \( \hat{\theta}_C \). Examples of this cost are given in Table 3.4. The
Table 3.2: Savings when two stations are owned by the same firm vs. operating separately

<table>
<thead>
<tr>
<th>Market</th>
<th>Los Angeles</th>
<th>Knoxville</th>
<th>Bismarck</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>13m</td>
<td>.7m</td>
<td>100k</td>
</tr>
<tr>
<td>Savings per year</td>
<td>$4.4m</td>
<td>$.23m</td>
<td>$34k</td>
</tr>
</tbody>
</table>

Table 3.3: Total cost savings created by mergers after 1996, compared to demand effects from Jezioriski (2010)

<table>
<thead>
<tr>
<th>Impact of Telecom Act</th>
<th>Consumer Surplus</th>
<th>Advertiser Surplus</th>
<th>Fixed Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>+1%</td>
<td>-$300m</td>
<td>-$2.450m</td>
</tr>
</tbody>
</table>

Table 3.4: Format switching cost for chosen markets

<table>
<thead>
<tr>
<th>Market</th>
<th>Los Angeles</th>
<th>Knoxville</th>
<th>Bismarck</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switching cost</td>
<td>$27m</td>
<td>$1.5m</td>
<td>$0.2m</td>
</tr>
</tbody>
</table>
3.6 Conclusions

This paper proposed a new estimator of a production cost curve that enables the identification of cost synergies from mergers. The estimation uses inequalities representing an equilibrium of a dynamic game with endogenous mergers and product repositioning decisions.

The biggest advantage of this estimator is that it enables the identification of the cost curve just from merger decisions, without using cost data. Since reliable cost data is very hard to obtain, the cost side analysis of mergers was very hard to perform. This method is able to solve this problem, and provides a powerful tool for policy makers to improve their merger assessments.

Since the proposed method is based on a fully dynamic framework, it additionally solves many of the problems of static merger analysis. First of all, endogenizing the merger decision allows for sample selection on unobservables in the estimation and correcting for the fact that only the most profitable mergers are carried out. Moreover, I allow for follow-up mergers and merger waves. Additionally, endogenizing product characteristics enables correction for post-merger product repositioning.

The estimator belongs to a class of indirect estimators proposed by Hotz, Miller, Sanders, and Smith (1994) and Bajari, Benkard, and Levin (2004). Therefore, it shares all the benefits of those estimators, such as conceptual simplicity of implementation and computational feasibility, because it avoids the computation of an equilibrium. However, it also shares their downsides, such as a loss in efficiency.

The estimator was applied to analyze the cost side benefits of a deregulation of the U.S. radio industry. It turns out that the consolidation wave in that industry between 1996 and 2006 provided substantial cost synergies. These amounted to about 2 billion dollars per year and constitute about 10% of industry revenue. Such benefits are an order of magnitude larger than potential losses in advertiser welfare found by Jezierski (2010). This provides a significant argument for the supporters of a deregulation bill, and serves as an example of how cost curve estimation can provide additional insights supplementing traditional merger analysis.
Appendix A

Additional material to Chapter 2

A.1 Advertising demand: Micro foundations

In this section I present a model that rationalizes inverse demand for advertising (2.5)

Assume that there are $A$ types of advertisers. Each type $a \in A$ targets a certain demographic group(s) $d_a$. Let $\gamma_2$ be a total mass of advertisers and $AS_a$ be a share of advertisers of type $a$ in market $m$. Advertisers are also heterogeneous in their value of the ad slot in format $f$, and I assume that those values are distributed uniformly on the interval $[0, \gamma_f]$. An advertiser of type $a$ gets utility only if a listener of type $d_a$ hears an ad. To compute the exact expected value of an advertising slot, advertisers need to know the demographic composition of each station in the market. Because advertisers are small, and such detailed data is not offered by Arbitron, it seems unlikely that they would be able to do that. Instead, I assume that they approximate those calculations using publicly available data contained in Arbitron’s Radio Today publications. These publications provide nation-wide conditional probabilities $r_{f|a}$ of a consumer of type $d_a$ choosing format $f$ conditional on listening to the radio. Advertisers take these conditional probabilities as given and compute the market specific probabilities of obtaining correct listeners when advertising in each format. Such computations can be done by Bayes’ Rule, i.e.

$$
r_{a|f} = \frac{r_{f|a}LS_a}{r_f}
$$
where $r_f = \sum_a r_{f|a} LS_a$ and $LS_a$ is the population share of demographic group $d_a$, which is assumed to be known to the advertiser. Having listeners’ distributions $r_{a|f}$ and station ratings $r_j$ (available on Arbitron’s website) at hand, advertisers compute the probability of successful targeting at station $j$ to be $r_j r_{a|f}$, where $f$ is a format of station $j$.

Radio stations quote costs-per-point $CPP_{af}$ individually for each advertiser type and format. Advertisers decide if they want to purchase advertising after observing the CPPs and station ratings. Because advertisers are small and likely do not have much market power over radio station owners, I assume that they are price and rating takers\(^1\). Advertisers can purchase advertising from several stations at once; however, I assume away any potential complementarities.

In equilibrium, advertisers purchase advertising as long as their expected value is above price. Let $q_a$ be the amount of advertising purchased by advertisers of type $a$. A marginal advertiser must be indifferent between purchasing advertising or not, so the clearing per-listener prices are given by

$$CPP_{af} = \gamma_{1f} r_{a|f} \left( 1 - \frac{1}{\gamma_2 AS_a} q_a \right)$$

Given the clearing prices $CPP_{af}$, advertisers are indifferent when choosing between formats, so I assume that advertising is purchased proportionally to the target listeners’ tastes i.e. $q_a = AS_a \sum_f r_{f|a} q_f$. If I make the simplifying assumption that $AS_a \approx LS_a$, then the arrival probability of an advertiser of type $a$ at a station of format $f$ would be equal to $r_{a|f}$. Therefore, expected per-listener price in format $f$ is given by

$$CPP_f = \sum_a (r_{a|f})^2 \gamma_{1f} \left( 1 - \frac{1}{\gamma_2} \sum_{f'} r_{f'|a} q_{f'} \right) =$$

$$= \gamma_{1f} \left( \sum_a (r_{a|f})^2 \right) \left( 1 - \frac{1}{\gamma_2} \sum_f q_f \left( \sum_a (r_{a|f})^2 \right)^{-1} \sum_a (r_{a|f})^2 r_{f|a} \right).$$

\(^1\)This assumption is is motivated by the fact that about 75% is purchased by small local firms. Such firms’ advertising decisions are unlikely to influence prices and station ratings in the short run.
Finally, I obtain Equation (2.5)

\[ p_j = \theta_1^A r_j \left( 1 - \theta_2^A \sum_{j' \in F} w_{jj'} q_{j'} \right) \]

by setting \( \omega_{jj'} = \left( \sum_a (r_{a|f})^2 \right)^{-1} \sum_a (r_{a|f})^2 r_{j'|a} \), \( \theta_2^A = \frac{1}{\gamma_2} \) and assuming that \( \theta_1 = \gamma_1 f \sum_a (r_{a|f})^2 \) for all \( f \). The last assumption basically means that niche formats (with listenership concentrated in one demographic bin) are less profitable for advertisers than general interest formats.

The presented model is only one of a number of ways to rationalize the weighted price equation (2.5) in which competition between formats is channeled though demographics. Other possibilities include: a local monopoly in which each advertiser type draws utility only from advertising on one particular station, and a format-monopoly in which each advertiser type targets only one format.

### A.2 Numerical considerations

To solve the optimization problem (2.12), I used a version of the Gauss-Newton method implemented in the commercial solver KNITRO. Using this state-of-the-art solver avoids certain convergence problems that are common to many non-linear estimators.

The iteration step of the KNITRO solver requires computing constraints, a Jacobian of the constraint, and an inverse of the inner product of this Jacobian (used to compute the approximate Hessian of the Lagrangian). The objective function and its Jacobian come essentially for free because of their simple nature.

To compute the constraints and their Jacobian, I employed a piece of highly optimized parallel C code. This allows the use a fairly large dataset (about 42,000 observations) and many draws (500 draws from Normal and CPS per date/market) when computing the constraints. When parallelizing the code, I was careful to maintain independence of the draws within and between threads. To achieve this, I implemented a version of a pseudo-random number generator (described in (L’Ecuyer and
Andres 1997). This generator enables us to create a desired number of independent pseudo-random feeds for each thread.

One iteration of the solver takes about two to three minutes on an 8-Core 3Ghz Intel Xeon processor and uses about 4GB of memory. About 90% of this computation is the inversion of a Hessian estimator within the KNITRO solver. This inversion cannot be parallelized because it is done inside the solver, without the user’s control.
Appendix B

Additional material to Chapter 3

B.1 Estimation without acquisition prices

In case the pricing function $\hat{P}_{jk}$ cannot be estimated in the first state because of data constraint, one could employ a bargaining model for infer it. Suppose one employs a parametrization $\hat{P}(\omega|\theta_P)$. For an initial value of parameters $\theta^0_P$ one could compute a surplus from acquisition of the product $j$ by an owner $k$ using simulated $\hat{V}_k^t$ and $\hat{V}_{k'}^t$ where $k'$ is the current owner of product $j$. Then using a bargaining model one could infer prices and fit a new parametrization $\theta^1_P$. If repeating this procedure leads to convergence, then obtain a parametrization $\hat{\theta}_P$ and value functions $\hat{V}_k^t$ that are consistent with eachother. The detailed description of this procedure is given in the Algorithm 1. The big downside of this approach is that one needs resolve this procedure for any set of cost parameters and cannot take advantage of linearing of the value function. It makes the procedure infeasible to use for large datasets because of computational burden. However, given the rapid hardware development it is reasonable to think it it would be feasible in the near future.
Algorithm 1: Estimator without price data

Take any $\theta_0^r$;
Let $r = 0$;
repeat
    Simulate the value functions $\hat{V}^r$ using pricing process $\hat{P}(\omega|\theta^r_P)$;
    Compute surplus from any acquisition using the simulated value functions;
    Compute acquisition prices $\hat{P}_{jm}$ by applying any bargaining game;
    Fit new parameters $\theta_{r+1}^P$ using $\hat{P}_{jm}$;
until convergence of $\theta^r_P$;

B.2 Radio acquisition and format switching algorithms

This section of the appendix contains a detailed flows of the algorithms used to simulate the value function from section 3.5.

Algorithm 2: Merger algorithm

Let $\omega^r_1 = s^r$;
foreach firm $k$ in a sequence $I(s^r)$ do
    Let $J_{-k}$ be a set of stations not owned by $k$ sorted by $\xi_j^r$;
    foreach station $j$ in $J_{-k}$ do
        Set purchase price $P_{jk}^r = \bar{P}^m$;
        Compute acquisition probability $\hat{\text{Prob}}^M(\omega_k^r, d^r)$;
        Draw a random number $u$ from $U[0, 1]$;
        if $u \leq \hat{\text{Prob}}^M$ then
            Increase $A_{\text{old owner}}^r$ by $\beta^{r-t}P_{jk}^r$;
            Decrease $A_k^r$ by $\beta^{r-t}P_{jk}^r$;
            Update $\omega_k^r$ for acquisition;
            Increase $B_k^r$ by $\beta^{r-t}E[\phi|\text{acquisition}]$;
        end
    end
Let $\omega^r_{k+1} = \omega^r_k$;
end
Algorithm 3: Format switching algorithm

Let $\tilde{\omega}_{r+1}^k = \omega_{K+1}^k$;

forall firm $k$ in a sequence $I(s^r)$ do
  Let $J_k$ be a set of stations owned by $k$ sorted by $\xi_j^r$;
 forall station $j$ in $J_k$ do
    Compute repositioning probabilities $\hat{\text{Prob}}_k^R(\tilde{\omega}_r^k, d_r^r)$;
    Simulate the future characteristic $f_j^{r+1}$;
    Increase $C_r^k$ by $\beta - t E[\psi|f_j^r]$;
    if the $f_j$ changed then
      Update $\tilde{\omega}_r^k$;
      Remember the repositioning for a computation of $D_r^k$;
    end
  end
Let $\tilde{\omega}_{tm}^{t+1} = \tilde{\omega}_{tm}^t$;
end

B.3 Policy function covariates

This section of the appendix contains tables of covariates used in the first stage in
the estimation in section 3.5.

<table>
<thead>
<tr>
<th>Format switching strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>PUR</td>
</tr>
<tr>
<td>FM</td>
</tr>
<tr>
<td>FORMAT</td>
</tr>
<tr>
<td>PORT_F</td>
</tr>
<tr>
<td>PORT_COMPJ_F</td>
</tr>
<tr>
<td>XI_PORT_F</td>
</tr>
<tr>
<td>XI_PORT_COMPJ_F</td>
</tr>
<tr>
<td>-</td>
</tr>
</tbody>
</table>

Table B.1: Covariates for the format switching strategy multinomial logic regression.
**Purchase strategy**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>OWNER1...OWNER4</td>
<td>Dummies that are equal to the ranking of the player in terms of total market share of owned stations. If ranking is lower than 4 we activate the fourth dummy</td>
</tr>
<tr>
<td>PAST_OWNER1...PAST_OWNER4</td>
<td>Ranking of the previous owner of the station amongst the competitors.</td>
</tr>
<tr>
<td>TRIAL</td>
<td>Describes how many stations did this player considered to purchase already this period. For explanation of sequential purchase decision process look in Section 3.5.3</td>
</tr>
<tr>
<td>PURO...PUR3</td>
<td>Dummies describing number of stations already purchased</td>
</tr>
<tr>
<td>FORMAT</td>
<td>Number of stations owned in the format of considered station</td>
</tr>
<tr>
<td>FORMAT_COMP1...FORMAT_COMP4</td>
<td>Number of stations owned by competitors in the considered station, by ranking. FORM COMP4 are pooled competitors with ranking of 4 or higher</td>
</tr>
<tr>
<td>FM</td>
<td>AM/FM dummy, equals to 1 if considered station is FM</td>
</tr>
<tr>
<td>PORT_F</td>
<td>Number of stations owner in format F</td>
</tr>
<tr>
<td>PORT_COMPJ_F</td>
<td>Number of stations competitor J owns in format F, competitors of ranking 4 or higher are pooled</td>
</tr>
<tr>
<td>XI</td>
<td>Average quality of stations owned in the format of considered station</td>
</tr>
<tr>
<td>XI_COMP1...XI_COMP4</td>
<td>Average quality of stations owned by competitors in the considered station, by ranking. XI COMP4 are pooled competitors with ranking of 4 or higher</td>
</tr>
<tr>
<td>XI_PORT_F</td>
<td>Average quality of stations owner in format F</td>
</tr>
<tr>
<td>XI_PORT_COMPJ_F</td>
<td>Average quality of stations competitor J owns in format F, competitors of ranking 4 or higher are pooled</td>
</tr>
</tbody>
</table>

- Dummies of the format of considered station interacted with demographic characteristics of the market

**Table B.2**: Covariates for the purchase strategy logic regression.
B.4 First stage estimates: Dynamic model

<table>
<thead>
<tr>
<th></th>
<th>Top 1 Owner</th>
<th>Top 2 Owner</th>
<th>Top 3 Owner</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buyer</td>
<td>0.5127</td>
<td>0.3423</td>
<td>0.2608</td>
</tr>
<tr>
<td>Seller</td>
<td>−0.3772</td>
<td>−0.2792</td>
<td>−0.0257</td>
</tr>
</tbody>
</table>

Table B.3: Station purchase policy estimates - buyer/seller dummies

<table>
<thead>
<tr>
<th></th>
<th>Estimator</th>
</tr>
</thead>
<tbody>
<tr>
<td>PUR0</td>
<td>−2.6082</td>
</tr>
<tr>
<td>PUR1</td>
<td>0.7548</td>
</tr>
<tr>
<td>PUR2</td>
<td>0.4279</td>
</tr>
<tr>
<td>PUR3</td>
<td>0.2463</td>
</tr>
<tr>
<td>FORMAT</td>
<td>−0.0534</td>
</tr>
<tr>
<td>FORMAT_COMP1</td>
<td>−0.0038</td>
</tr>
<tr>
<td>FORMAT_COMP2</td>
<td>−0.0556</td>
</tr>
<tr>
<td>FORMAT_COMP3</td>
<td>0.0728</td>
</tr>
<tr>
<td>FORMAT_COMP4</td>
<td>−0.0428</td>
</tr>
<tr>
<td>FM</td>
<td>0.0151</td>
</tr>
<tr>
<td>STATION_XI</td>
<td>−0.1069</td>
</tr>
<tr>
<td>XI</td>
<td>0.0596</td>
</tr>
<tr>
<td>XI_COMP1</td>
<td>0.0270</td>
</tr>
<tr>
<td>XI_COMP2</td>
<td>0.0712</td>
</tr>
<tr>
<td>XI_COMP3</td>
<td>0.0767</td>
</tr>
<tr>
<td>XI_COMP4</td>
<td>−0.0117</td>
</tr>
</tbody>
</table>

Table B.4: Station purchase policy estimates - other variables
### APPENDIX B. ADDITIONAL MATERIAL TO CHAPTER 3

#### Table B.5: Format switching policy estimates - format dynamics

<table>
<thead>
<tr>
<th>PURCHASE</th>
<th>AC</th>
<th>Rock</th>
<th>CHR</th>
<th>Urban Alt.</th>
<th>News Talk</th>
<th>Country</th>
<th>Spanish</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>FM</td>
<td>0.30</td>
<td>-0.14</td>
<td>0.04</td>
<td>-0.07</td>
<td>0.05</td>
<td>0.03</td>
<td>-0.23</td>
<td>-0.22</td>
</tr>
<tr>
<td>AC</td>
<td>1.26</td>
<td>1.54</td>
<td>1.35</td>
<td>1.06</td>
<td>-0.25</td>
<td>1.31</td>
<td>0.56</td>
<td>0.85</td>
</tr>
<tr>
<td>Rock</td>
<td>3.70</td>
<td>-0.47</td>
<td>-0.34</td>
<td>-0.86</td>
<td>-0.43</td>
<td>0.37</td>
<td>-0.66</td>
<td>-0.44</td>
</tr>
<tr>
<td>CHR</td>
<td>-0.27</td>
<td>4.41</td>
<td>-0.58</td>
<td>-0.18</td>
<td>-0.10</td>
<td>0.48</td>
<td>-0.32</td>
<td>-0.21</td>
</tr>
<tr>
<td>Urban Alt.</td>
<td>-0.24</td>
<td>-0.42</td>
<td>4.38</td>
<td>-0.06</td>
<td>-0.19</td>
<td>0.00</td>
<td>-0.14</td>
<td>-0.35</td>
</tr>
<tr>
<td>News Talk</td>
<td>-0.49</td>
<td>0.05</td>
<td>-0.35</td>
<td>4.06</td>
<td>-0.17</td>
<td>0.48</td>
<td>-0.15</td>
<td>-0.22</td>
</tr>
<tr>
<td>Country</td>
<td>-1.14</td>
<td>-1.01</td>
<td>-1.06</td>
<td>-1.35</td>
<td>-0.63</td>
<td>4.76</td>
<td>-0.73</td>
<td>-1.15</td>
</tr>
<tr>
<td>Spanish</td>
<td>-1.61</td>
<td>-1.45</td>
<td>-1.30</td>
<td>-1.61</td>
<td>-1.20</td>
<td>-0.29</td>
<td>3.10</td>
<td>-1.42</td>
</tr>
<tr>
<td>Other</td>
<td>-0.89</td>
<td>-1.07</td>
<td>-1.31</td>
<td>-1.27</td>
<td>-0.86</td>
<td>0.00</td>
<td>-1.22</td>
<td>3.02</td>
</tr>
<tr>
<td>Dark</td>
<td>-2.18</td>
<td>-2.42</td>
<td>-2.50</td>
<td>-2.62</td>
<td>-1.61</td>
<td>-0.72</td>
<td>-1.60</td>
<td>-1.31</td>
</tr>
</tbody>
</table>

#### Table B.6: Format switching policy estimates - current demographics

<table>
<thead>
<tr>
<th>Age</th>
<th>AC</th>
<th>Rock</th>
<th>CHR</th>
<th>Urban Alt.</th>
<th>News Talk</th>
<th>Country</th>
<th>Spanish</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>12-17</td>
<td>0.00</td>
<td>-0.27</td>
<td>0.04</td>
<td>-0.50</td>
<td>-0.33</td>
<td>-0.67</td>
<td>-0.50</td>
<td>-0.32</td>
</tr>
<tr>
<td>18-24</td>
<td>0.00</td>
<td>-0.31</td>
<td>-0.26</td>
<td>-0.69</td>
<td>0.31</td>
<td>0.00</td>
<td>-0.42</td>
<td>-0.36</td>
</tr>
<tr>
<td>25-34</td>
<td>-0.54</td>
<td>0.00</td>
<td>0.02</td>
<td>-0.37</td>
<td>-0.14</td>
<td>-0.99</td>
<td>-0.06</td>
<td>-0.32</td>
</tr>
<tr>
<td>35-44</td>
<td>-0.48</td>
<td>-0.00</td>
<td>-0.20</td>
<td>-0.32</td>
<td>-0.06</td>
<td>-1.17</td>
<td>-0.42</td>
<td>-0.08</td>
</tr>
<tr>
<td>45-49</td>
<td>-0.46</td>
<td>0.00</td>
<td>-0.93</td>
<td>-0.61</td>
<td>0.23</td>
<td>-0.89</td>
<td>-0.81</td>
<td>-0.09</td>
</tr>
<tr>
<td>50-54</td>
<td>-0.44</td>
<td>-0.41</td>
<td>-1.36</td>
<td>-0.67</td>
<td>0.42</td>
<td>-0.82</td>
<td>-0.62</td>
<td>-0.09</td>
</tr>
<tr>
<td>55-64</td>
<td>0.00</td>
<td>-0.64</td>
<td>-1.49</td>
<td>-0.68</td>
<td>0.34</td>
<td>-0.77</td>
<td>-0.42</td>
<td>-0.16</td>
</tr>
<tr>
<td>Gender</td>
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<td>-0.23</td>
<td>-0.43</td>
<td>-0.54</td>
<td>-0.00</td>
<td>-0.84</td>
<td>-0.34</td>
<td>-0.21</td>
</tr>
<tr>
<td>Some HS</td>
<td>-0.38</td>
<td>-0.49</td>
<td>-0.41</td>
<td>-0.33</td>
<td>-0.27</td>
<td>-0.13</td>
<td>0.06</td>
<td>0.02</td>
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<td>0.00</td>
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<td>-0.32</td>
<td>-0.84</td>
<td>-0.29</td>
<td>-0.90</td>
<td>-0.19</td>
</tr>
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<td>Some College</td>
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<td>-0.34</td>
<td>-0.72</td>
<td>-0.70</td>
<td>0.23</td>
<td>-0.45</td>
<td>-0.45</td>
<td>-0.03</td>
</tr>
<tr>
<td>Income 0-25k</td>
<td>-0.16</td>
<td>-0.83</td>
<td>-0.32</td>
<td>-0.13</td>
<td>-0.35</td>
<td>-0.43</td>
<td>-0.52</td>
<td>-0.03</td>
</tr>
<tr>
<td>Income 25k-50k</td>
<td>-0.06</td>
<td>-0.54</td>
<td>0.14</td>
<td>-0.39</td>
<td>-0.33</td>
<td>-0.34</td>
<td>-0.13</td>
<td>0.00</td>
</tr>
<tr>
<td>Income 50k-75k</td>
<td>-0.07</td>
<td>-0.02</td>
<td>-0.54</td>
<td>-0.22</td>
<td>0.21</td>
<td>-0.39</td>
<td>-1.10</td>
<td>-0.17</td>
</tr>
<tr>
<td>Black</td>
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<td>-0.58</td>
<td>0.00</td>
<td>1.25</td>
<td>-0.44</td>
<td>-1.11</td>
<td>-0.54</td>
<td>-0.26</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.55</td>
<td>0.19</td>
<td>-0.36</td>
<td>-0.06</td>
<td>-0.49</td>
<td>-0.20</td>
<td>2.42</td>
<td>-0.56</td>
</tr>
</tbody>
</table>
### Table B.7: Format switching policy estimates - demographic dynamics

<table>
<thead>
<tr>
<th>Age 12-17</th>
<th>AC</th>
<th>Rock</th>
<th>CHR</th>
<th>Urban Att.</th>
<th>News Talk</th>
<th>Country</th>
<th>Spanish</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age 18-24</td>
<td>−7.73</td>
<td>3.44</td>
<td>17.89</td>
<td>0.00</td>
<td>0.00</td>
<td>−12.76</td>
<td>0.00</td>
<td>6.06</td>
</tr>
<tr>
<td>Age 25-34</td>
<td>4.29</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>−1.35</td>
<td>5.23</td>
<td>4.32</td>
<td>−3.59</td>
</tr>
<tr>
<td>Age 35-44</td>
<td>2.65</td>
<td>0.00</td>
<td>5.23</td>
<td>1.83</td>
<td>−4.83</td>
<td>0.00</td>
<td>2.67</td>
<td>1.73</td>
</tr>
<tr>
<td>Age 45-49</td>
<td>−3.31</td>
<td>0.00</td>
<td>9.04</td>
<td>0.00</td>
<td>2.31</td>
<td>−3.45</td>
<td>−2.98</td>
<td>2.59</td>
</tr>
<tr>
<td>Age 50-54</td>
<td>−3.27</td>
<td>0.00</td>
<td>−2.60</td>
<td>−1.95</td>
<td>1.63</td>
<td>0.04</td>
<td>−3.37</td>
<td>0.00</td>
</tr>
<tr>
<td>Age 55-64</td>
<td>−4.57</td>
<td>−3.19</td>
<td>−7.50</td>
<td>0.00</td>
<td>7.73</td>
<td>0.00</td>
<td>−1.12</td>
<td>0.00</td>
</tr>
<tr>
<td>Gender</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Some HS</td>
<td>−0.03</td>
<td>−0.06</td>
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Bibliography


