

**Radio Airplay and the Record Industry:  
An Economic Analysis**

By

James N. Dertouzos, Ph.D.

For the  
National Association of Broadcasters

Released June 2008

## Table of Contents

About the Author and Acknowledgements .....	3
Executive Summary .....	4
Introduction and Study Overview .....	7
Overview of the Music, Radio and Related Media Industries .....	15
Previous Evidence on the Sales Impact of Radio Exposure .....	31
An Econometric Analysis of Radio Airplay and Recording Sales .....	38
Summary and Policy Implications .....	71
Appendix A: Options in Dealing with Measurement Error .....	76
Appendix B: Supplemental Regression Results .....	84

## **About the Author and Acknowledgements**

### **About the Author**

Dr. James N. Dertouzos has more than 25 years of economic research and consulting experience. Over the course of his career, Dr. Dertouzos has conducted more than 100 major research projects. His Ph.D. is in economics from Stanford University. Dr. Dertouzos has served as a consultant to a wide variety of private and public sector organizations including radio and television broadcasters, cable television, newspapers, industry associations and law firms in matters related to regulation, anti-trust and other legal issues. His research and publications cover a wide range of public policy issues including the industrial organization of mass media, public sector management and military manpower. Dr. Dertouzos has worked for the National Bureau of Economic Research, the Bureau of Labor Statistics, the University of Santa Clara, Stanford University, the University of California at Los Angeles, the Annenberg School of Communications at the University of Southern California and the RAND Corporation.

### **Acknowledgements**

The author wishes to thank Arbitron for providing local radio music listening/ratings data for all radio stations in the United States and for connecting him with Act 1 Systems, Inc. Thanks go to BIA Financial Network for providing radio financial data, Nielsen BDS and Mediaguide for providing spins data (volume of music played) and Nielsen SoundScan for providing music sales data. The author also wishes to thank the people at these organizations for taking the time to review and comment on the study reported here. This complex project would not have been possible without the data and assistance each provided.

# **Radio Airplay and the Record Industry: An Economic Analysis**

## **Executive Summary**

**By James N. Dertouzos, Ph.D.**

For decades, radio has provided programming to listeners free of charge, introducing its audiences to new types of music entertainment and new recording artists. It is widely believed that radio stations, record labels and recording artists enjoy a symbiotic relationship, meaning, the record industry utilizes radio to promote its artists and music to hundreds of millions of radio listeners<sup>1</sup>, while radio attracts listeners and advertisers by airing this recorded music.

Generally, radio's music promotion is understood to stimulate the purchase of recordings, merchandise and concert tickets by the listening audience. However, while this benefit is widely acknowledged, until this study was conducted its subsequent value had not been adequately quantified using rigorously applied econometric research methods. The primary question this study addresses is whether the symbiotic relationship between radio and the record industry provides promotional value to music record labels and recording artists. And, if so, what level of promotional value do artists and record labels receive from radio stations airing their music?

To answer these questions, this study examines the relationship between radio airplay of music and sales of albums and digital tracks from 2004 to 2006 in the 99 largest designated market areas (DMAs). Econometric models were developed to address the relationship between music sales and variations in music exposures, while controlling for a variety of local market factors that may affect music sales and radio listening,

---

<sup>1</sup> Radio reaches 233 million listeners every week, including 82 percent of all people 12 and older, according to Arbitron's RADAR 95 report, December, 2007.

including audience demographic and economic characteristics. The most appropriate measure for music exposures is used in these models -- the number of listeners multiplied by the number of “spins” or plays of a music track. Five versions of the model were tested, allowing for a variety of methodologies and underlying assumptions. The empirical results for all versions were quite similar, demonstrating that the findings and their policy implications are robust and highly reliable.

This study clearly demonstrates that radio airplay increases music sales and that performing artists and record labels profit from exposure provided by radio airplay. Findings demonstrate that a significant portion of music industry sales of albums and digital tracks can be attributed to radio airplay – at minimum 14 percent and as high as 23 percent. These results show that radio is providing the record industry with significant, incremental sales revenues or promotional sales benefit that ranges from \$1.5 to \$2.4 billion annually. The study shows that music played on the radio affects music sales more than other factors, including local demographics such as age, race, geographical location and income. Further, the impact estimated from exposure to music on the radio is shown to be positive and significant for all music genres and radio formats.

The range of promotional value identified is a conservative estimate. While this study focuses on albums and tracks as a first step in analyzing the promotional value of radio airplay, it does not take into account concert ticket and merchandise sales or licensing revenue. Future studies might attempt to include these additional factors given their high monetary contribution to record industry revenues. Billboard, for example, reported more than \$2.8 billion in concert ticket and attendance revenues for 2006.<sup>2</sup> If these concert ticket revenues had been part of the current study’s econometric modeling, the promotional value from radio play of music would likely have been higher.

As the record industry advocates for direct payment from radio stations to music labels and artists through a new performance fee, it should be noted that disturbing the current symbiotic relationship that is found to exist between radio and the record industry

---

<sup>2</sup> Billboard.biz, “Touring Biz Soars in 2006, Ray Waddell, Nashville ONLINE, 13 December 2006.

could actually harm, not help, all parties. If a new performance fee were enacted, stations could reduce the amount of music airplay, change formats and even cease to operate, resulting in the loss of much of this promotional benefit.

## **1. Introduction and Study Overview**

Does radio airplay provide the music industry with free promotional or advertising value? Conventional wisdom, the way the marketplace functions, and previous evidence, in the form of survey research and the persistence of standard music industry practices to promote radio airplay, all suggest that radio airplay stimulates the sale of recordings as well as box office and merchandise revenues earned from concert tours. However, until now, little high quality, empirical research has been conducted to address this question.

Recent research conducted on this issue has been flawed because of poor methodology, failure to include important data, and interpretation of results using an inappropriate market context. The study presented here is designed to address these methodological challenges by using an appropriate measure of radio exposure, correcting data deficiencies found in former studies and by utilizing an appropriate study design that precluded finding spurious correlations.

The following rigorous, econometric analysis utilizes models that account for demographic and economic market characteristics that can affect the relationship between radio airplay and the purchase of music. The models indicate that radio airplay does, indeed, provide the recording industry with free promotion or advertising of its music. These results are especially noteworthy because of their magnitude, their high statistical significance and because they are remarkably insensitive to a variety of econometric methods, assumptions, and measurement techniques.

### The Media Marketplace

For decades, a symbiotic relationship has existed between the radio and recording industries. More than 70 percent of the nation's radio stations compete in the media marketplace by providing free, over-the-air music entertainment to listeners. Although composers and publishers receive royalties for the performance of such music, record labels and performing artists do not receive direct payment for use of their sound recordings. Instead, performers and record labels profit indirectly from the exposure provided by radio airplay, through the reproduction, distribution, and sale of music

recordings. Under this arrangement, both the radio and recording industries expect to profit. The recording industry receives indirect revenues when audiences like and purchase the music they hear. Local radio stations receive revenues from advertisers that pay for access to listeners who are potential customers for the goods and services they offer. Here we see the results of a mutually beneficial relationship between local radio broadcasters and the recording industry: a stimulation of music consumption and the generation of value for local radio and its advertisers.

Other media platforms similarly function without direct compensation. For example, daily newspapers are sold at prices that fail to compensate publishers for the cost of the paper on which they are printed. Instead, revenues come not only from subscriptions and single copy sales but also from advertising sales, with advertising accounting for 80 percent of total revenues. Recently, some recording artists have begun to offer Internet listeners downloads of their music tracks without charge. The motivation is to stimulate interest in their live concerts, which typically bring in more revenue than the sale of their recordings.

#### The Evolving Media Landscape

Although it is widely believed that free advertising in the form of radio airplay stimulates the sale of recordings, as well as box office and merchandise revenues earned from concert tours, new technologies are changing the media landscape, and old questions are being asked anew about this symbiotic relationship between radio and the recording industry. In particular, the question of whether local radio should pay direct compensation in the form of performance fees to performers and record labels is being resurrected. This ongoing debate is being stimulated by changing market conditions, including significant declines in the sales of CDs, proliferation of new digital technologies (MP3 players, broadband access, Internet radio, etc.) and perceived future risks associated with new patterns of media use observed in younger demographic groups.

The last decade has been a turbulent one for the recording industry. Beginning with Napster and the associated onslaught of unauthorized downloading, there has been a steady erosion of industry revenues. Although legal and regulatory mechanisms have



emerged to slow the losses, the industry still faces significant risks. Digital technologies, alternative distribution channels, changes in consumer behavior and a reduction in market entry barriers all threaten the dominance of the major record labels. In this increasingly competitive environment, record labels seek new revenue streams to make up for revenue lost from CD sales. This has resulted in a recent seismic industry shift towards so-called “360 deals” between record labels and performers,<sup>3</sup> as well as a renewed interest in exacting monetary payment from local radio stations.

However, these recent changes in production, distribution, and consumer behavior patterns also hold promise for the future of the recording industry. The explosion of digital sales, the proliferation of MP3 players, Internet activity, and the comfort of younger generations with new technologies, suggest that new opportunities for profit abound. Although the two billion dollar decline in CD sales from 2004 to 2006 is not yet offset by the \$878 million in digital download revenues in 2006,<sup>4</sup> these figures are somewhat misleading, since the profit margins generated by digital sales are larger than those associated with physical CD sales, and digital sales are increasing exponentially. Further, there are no longer physical constraints on inventory. Thus, independent artists are no longer restricted by a store’s ability to carry expanded inventories that may or may not include their recordings. Combining these new opportunities for artists and record labels to succeed in the competitive marketplace with cost savings due to digital distribution, it is easy to conclude that potential revenue from paid digital downloading bodes well for the future of the recording industry.

#### Related Economic Theory and Earlier Research

Given this changing media landscape, what promotional value does radio provide to performers and record labels by playing their recordings to wide audiences at no cost? While the answer to this question might seem intuitively clear, the renewed debate about this question suffers from an absence of rigorous research.

---

<sup>3</sup> A 360 deal is a contract that allows a record label to receive a percentage of the earnings from all of a band’s activities (concert revenue, merchandise sales, endorsement deals, etc.) instead of just record sales. [http://www.economist.com/business/PrinterFriendly.cfm?story\\_id=9443082](http://www.economist.com/business/PrinterFriendly.cfm?story_id=9443082)

<sup>4</sup> Recording Industry Association of America, Music Industry Sales, Digital Downloads, 2004-2006

The goal of this study is to begin to fill this research void by providing answers to fundamental questions, such as whether radio airplay provides a promotional benefit or value to the recording industry, and if so, whether this value would be reduced by the adoption of performance fees.

Of course, the impact of performance fees depends on their structure. Thus, as a first step to answering these questions, various performance fee schemes were explored. The possible schemes addressed included flat fees based on station size, fees based on the quantity of music played, fees based on music exposures (spins times audience), and fees based on revenues. Based on economic principles, one can conclude that all of the possible schemes would reduce the profits of radio stations as well as the welfare of their listeners. However, the impact on artists, consumers of recorded music, and even the major record labels would depend on market factors that are not well understood, including whether and how much radio airplay impacts music sales.

One of these schemes, a fee based on the annual revenues of a radio station – essentially a revenue-based tax – would probably not cause stations to alter the quantity of music aired in order to reduce their financial burden. Such a scheme can be viewed as a pure transfer of revenues from radio stations to the music industry. Relative to other options, this type of revenue-based fee is likely to be favored by the music industry if its goal is to gather the most fees possible while at the same time maintain the same level of music exposures. Ironically, however, by endorsing such a revenue-based fee, the music industry is implicitly acknowledging that radio airplay has a positive effect on music sales.

Another scheme, which is currently used for determining performance fees for streaming of music played on digital platforms, is based on total music exposure (number of played tracks or spins times the number of listeners). This option is the equivalent of a progressive tax, because the magnitude of the fee increases with the volume of music played. As music increases ratings, the payment per track increasingly becomes a function of the quantity of music played. Thus, when radio airplay has a positive promotional effect, this approach is likely to be very ineffective because the revenue transfer is achieved at very high cost to all industry participants, including the record labels and artists. This approach also penalizes music stations that invest in high-quality

news, talk, or other non-music programming because such programming would increase ratings and thereby increase the fee levied on music played. This diminishes a station's incentive to invest in quality programming of all types. Not only would music play decrease, but quality non-music content would decrease as well. Ratings would diminish and listeners would suffer. Indeed, when music played on the radio has a positive impact on music sales, then the record industry will be damaged as well.<sup>5</sup>

### Related Empirical Studies

Although the foregoing economic schemes demonstrate the potential impact of performance fees, they do not provide hard evidence that airplay of music affects music sales. Therefore, we reviewed relevant performance fee research studies. Again, conventional wisdom is that radio airplay stimulates record sales.<sup>6</sup> This belief is consistent with the anecdotal evidence, including the fact that record labels pay large sums to promote their releases and garner radio airplay. Unfortunately, there has been precious little scholarly research on this topic,<sup>7</sup> and the two most recent contributions to the literature have contrasting conclusions. A study by Montgomery and Moe (2002) examines the empirical relationships between weekly sales volumes for a sample of new album releases and radio airplay of those tracks. The results of this study are consistent with conventional wisdom, survey data and industry practices. In particular, it finds that sales of individual albums are promoted by radio airplay. A second more recent study, by Liebowitz (2007), examines aggregate sales of albums in the top 100 designated

---

<sup>5</sup> In earlier research, Dertouzos and Wildman (1979) developed a simple but general model of radio program choice. They considered a scheme based on the volume of radio airplay time. They formally demonstrated the obvious, that such fees could motivate broadcasters to reduce the amount of music played. Such reductions would harm broadcasters, their listeners, copyright owners, and likely consumers of recorded music.

<sup>6</sup> As Bard and Kurlantzick (1974), p. 95 noted: "It is an accepted fact that radio play stimulates record sales by exposing new releases to potential buyers; in other words, radio play advertises records."

<sup>7</sup> As Sidak and Kronemyer (1987) observe "There appears to be no published study confirming this complementary demand relationship, let alone estimating its empirical magnitude." On the other hand, there exists a larger base of research examining the impact of file sharing and illegal downloading on record sales. These efforts face the same technical challenges that burden studies of the impact of radio play. However, they are also hampered by the absence of reliable data on file sharing or illegal downloading. One of the more creative attempts to estimate the impact of digital downloading can be found in Robb and Waldfogel (2006). Their analysis utilizes data on individual college students and takes advantage of contrasting university Internet access policies that provide exogenous variation in the volume of downloading. Still, despite these best efforts, the resulting evidence is very mixed and sensitive to alternative approaches and assumptions.

market areas (DMAs). He examines changes between 1998 and 2003 in album sales and estimates the impact of changes in Arbitron ratings for stations with music formats. In contrast to the Montgomery and Moe findings, Liebowitz finds a large *negative* effect at an industry level.

Although both studies suffer from certain flaws, the Montgomery and Moe study is the more reliable of the two. The data errors and methodological choices made in the Liebowitz study are problematic. He does not adequately account for population and/or audience distributions across DMAs or station coverage areas. Further, the Liebowitz approach is inferior under the wide range of conditions likely to prevail, with the results dubious because of some unfounded assumptions about the pattern of regression errors. But, comparing the two studies provides a list of methodological challenges that need addressing in order to answer the key empirical question, namely whether radio airplay provides promotion value to performers and record labels.

#### Radio Airplay Economic Analysis

The specific objective of this study is to quantify the relationship between radio airplay and the sale of albums and digital tracks from 2004 to 2006 in the 99 largest DMAs in the United States.<sup>8</sup> An econometric approach was used to link sales of albums and digital tracks with variations in music exposures, while controlling for a variety of local market factors that might indirectly affect music purchases.<sup>9</sup>

Five econometric models were tested to determine the relationship between the sale of albums and digital tracks and exposure to music on local radio. Each of these five models indicated that music exposures had a positive and statistically significant impact

---

<sup>8</sup> Using all 100 DMAs available from Nielsen SoundScan is not a correct approach because one of those DMAs is an “all other” DMA market that is not contiguous and is geographically dispersed across the entire United States. Therefore, this study appropriately uses only the top 99 DMAs.

<sup>9</sup> These local market factors included demographic and economic characteristics such as gender, age, race/ethnicity, employment status, wages earned, industry employed in (retail, construction, etc.), market size, market location (East North Central region, Middle Atlantic region, etc.), Internet usage, and commuting time. Also included in the analysis were station characteristics such as class of license, signal power, and format. The measure shown in previous research to be the most appropriate measure for music exposure was used to calculate economic impact, that is, the number of listeners multiplied by the number of “spins” or plays of a music track. Music listening data were provided by Arbitron. Data on music album sales and digital downloads of tracks were provided by Nielsen SoundScan. Music spin data came from Nielsen BDS and Mediaguide. Demographic and economic data came from the Bureau of Labor Statistics and U.S. Census Bureau. Radio station characteristics and coverage data were provided by BIA Financial Network.

on retail music sales. Across all models, results were especially noteworthy because of their magnitude, their high statistical significance, and because they were remarkably insensitive to a variety of econometric methods, assumptions, and measurement techniques. Regression coefficient estimates across all categories of music sales (by music format) compared against music exposure from radio airplay were significant at the 99 percent level.

Results across the five models clearly demonstrated that performing artists and the record labels that represent them indirectly profit from radio airplay through the distribution and sale of sound recordings. Findings demonstrate that a significant portion of industry sales of albums and digital tracks can be attributed to radio airplay – at minimum 14 percent and as high as 23 percent. These results show that radio is providing the record industry with significant, incremental sales revenues or promotional sales benefit that ranges from \$1.5 to \$2.4 billion annually. Further, the impact estimated from exposure to music on local radio is positive and significant for all audiences and all markets.

Using simulations, the study also shows that music played on local radio affects music sales more than the individual impact of demographic characteristics such as age, race, geographical location, or income. The simulations show the impact on music sales due to one-standard deviation increase in music exposures. Using simulations is a standard technique for delving into the detailed findings that regression analyses provide. For album sales, simulations show that one-standard deviation increase in exposure to music played on local radio (equivalent to about ten additional tracks of music per day) result in a two percent increase in album sales. For digital tracks, one-standard deviation increase in exposure to music played on local radio results in a 2.4 percent increase in music sales. In addition, data show that the relationship between album and track sales and exposure to music on local radio varies by genre. Country music sales appear to be the most responsive, with radio airplay resulting in a 3.2 percent increase in music sales.

The simulations also showed that market demographic and economic factors clearly played a large role in the relationship between exposure to music on local radio and music sales. Coefficient estimates from the regression models were, for the most part, unsurprising in that they demonstrated support for intuitive assumptions about the

relationship between demographics, economic factors and radio airplay on music sales. For example, higher income people were more likely to purchase all types of music, and sales of tracks expanded the most when those with higher incomes were exposed to music on local radio. As might be expected, music sales were negatively related to unemployment. That is, the employed were more likely to purchase music after hearing music on the radio than the unemployed. With the exception of the Country format, sales of music were highest when retail wages were highest.

This study clearly demonstrates that radio airplay increases music sales. Economic theory indicates that new performance fees imposed on radio stations may induce stations to change program formats and the amount of music played. Some smaller stations could find a new fee too burdensome and go out of business. And, ultimately much of the promotional benefit determined through this study would be lost. As the recording industry advocates for direct payment from radio stations to music labels and artists through a new performance fee, it should be noted that disturbing the current symbiotic relationship that exists between radio and the record industry could actually harm, not help, all parties. If a new performance fee were enacted, stations could reduce the amount of music airplay, change formats and even cease to operate, resulting in the loss of much of the promotional benefit demonstrated in this study.

## 2. Overview of the Music, Radio and Related Media Industries

The mass media represent a number of interrelated industries that compete in multiple market settings for entertainment and advertising dollars. This section provides a summary overview of these industries for the purpose of providing context to the analysis of performance fees for radio play of recorded music. The section begins with a discussion of entertainment and advertising overall, identifies specific technology trends and concludes with a more detailed discussion of some of the important elements of the radio and music industries.

### *Media Overview*

The average person spent about 10 hours a day consuming a variety of media products in 2006. Overall, consumption has increased by about five percent since 2000. Television, including broadcast and cable television, remains the dominant medium, with over 40 percent of the total time spent with television. Time spent listening to the radio has increased over this time period. Dramatic increases are evident for home video and consumer Internet (not employment related). Over the same period, time spent listening to recorded music has fallen significantly. In 2000, the average consumer spent 258 hours a year, or just over 40 minutes daily, listening to recorded music. This number has fallen by nearly one-third since 2000.<sup>10</sup>

Table 2.1 presents average time spent on media per day (in hours) broken down by age. These data indicate higher levels of activity, primarily because they include business Internet uses. Music listening does not appear to be negatively correlated with radio play across demographic groups. For example, young persons between the ages of 15 and 17 are the most avid music listeners, whether the medium is radio or recorded music. Older demographics prefer television and are less likely to be music listeners, especially recorded music.

---

<sup>10</sup> Veronis Suhler Stevenson, N.Y., *Communications Industry Forecast & Report*, 2007, cited in Statistical Abstract of the United States 2007.

Table 2.1  
Average Time Spent on Media Per Day (in hours), by Age

	TV	Online	IM/E-Mail	Radio	Video Games	MP3/CD Music	Total
Total Adults	3.7	3.6	1.7	1.8	.9	.8	12.5
Age: 13-14	3.1	3.2	2.3	1.9	1.3	2.1	13.9
Age: 15-17	3.2	3.2	2.4	2.3	1.3	2.3	14.7
Age 18-24	3.4	3.5	2.0	1.7	1.2	1.6	13.4
Age 25-54	3.6	3.6	1.7	1.9	.9	.8	12.5
Age 55-64	4.1	3.5	1.6	1.4	.8	.3	11.7

Source: "Time Spent with TV, Online, E-Mail & IM, Radio, Gaming and MP3/CD," Data drawn from "The Myers Survey Defining the Emotional Connections of Media to Their Audiences," <http://www.mediavillage.com/jmr/2005/10/26/jmr-10-26-05>

Information on consumer expenditures is presented in Table 2.2. Total per capita expenditures were over \$888 in 2006. This represents nearly a 50 percent increase since 2000. It is interesting to note that the consumer price index rose by just over 17 percent over the same time period. Thus, real expenditures on media increased by over 35 percent. Recall that time spent on media rose by five percent in comparison. This disparity is difficult to interpret, because of the rather dramatic technology improvements and changes in the distribution of spending. Recorded music and daily newspapers were the only media that exhibited declines in nominal spending. For recorded music, we will see that this partially reflects changes in the composition of spending, with substitution of less expensive digital downloads for CDs. The most dramatic increases were in Internet, subscription television, and home video. In particular, consumer Internet fees doubled over this seven-year period.



These expenditure patterns do not reflect the time-use patterns observed earlier. This is because some of the media rely more heavily on advertising dollars.<sup>11</sup> Consumer expenditures either reflect regulatory limits on pricing or the relative merit of maximizing audiences vis-à-vis generating subscription revenues, or both.

As shown in Table 2.3, broadcast television relies exclusively on advertising and generates over \$46 billion in revenues annually. Daily newspapers earn about the same, with advertising accounting for about 80 percent of their total revenues. Internet advertising fell dramatically in the recession years following 9/11, but has increased since 2002.

Table 2.2  
Per Capita Expenditures on Entertainment Media 2000-2006

	2000	2002	2004	2006*	Change
Total	\$608.31	\$712.64	\$794.78	\$888.06	\$279.75
Cable and Sat TV	\$189.45	\$224.30	\$255.36	\$282.92	\$93.47
Broadcast and Sat Radio	\$0.00	\$0.07	\$1.15	\$4.68	\$4.68
Box office	\$32.64	\$39.59	\$38.76	\$39.11	\$6.47
Home video	\$81.49	\$108.22	\$125.31	\$151.09	\$69.60
Recorded Music	\$61.04	\$52.47	\$49.39	\$45.77	-\$15.27
Videogames	\$27.89	\$32.34	\$32.94	\$36.13	\$8.24
Consumer Internet	\$49.49	\$85.84	\$113.48	\$138.83	\$89.34
Daily Newspapers	\$51.93	\$53.00	\$51.62	\$48.97	-\$2.96
Consumer Magazines	\$47.54	\$46.86	\$46.88	\$47.59	\$0.05

\*Estimated

Source: Veronis Suhler Stevenson, N. Y., *Communications Industry Forecast & Report*, 2007, cited in *Statistical Abstract of the United States 2007*.

<sup>11</sup> Of course, television programmers and, to a lesser extent, radio programmers, have the option of distributing products through subscription-based media channels instead of offering them free over the air. Thus, for certain types of general interest programming, the potential for advertising revenue exceeds the potential for charging subscription prices, and it is made available to consumers at no cost so that audiences are maximized. This situation is analogous to the case of music programming being offered to radio stations at no cost.

Table 2.3  
Advertising Revenues by Medium, 2000-2006  
(\$ Millions)

	2000	2001	2002	2003	2004	2005	2006
Newspapers	49,050	44,255	44,031	44,843	46,614	47,335	46,555
Magazines	12,370	11,095	10,995	11,435	12,247	12,847	13,168
Broadcast TV	44,802	38,881	42,068	41,932	46,264	44,293	46,880
Cable	15,455	15,736	16,297	18,814	21,527	23,654	25,025
Radio	19,295	17,861	18,877	19,100	19,581	19,640	19,643
Yellow Pages	13,228	13,592	13,776	13,896	14,002	14,229	14,393
Direct Mail	44,591	44,725	46,067	48,370	52,191	55,218	58,642
Business Papers	4,915	4,468	3,976	4,004	4,072	4,170	4,195
Internet	6,507	5,645	4,883	5,650	6,853	7,764	9,100

Source: McCann Erickson Worldwide

Table 2.4 converts radio revenues to real dollars, but adjusts for inflation over the 2000-2006 periods. It is worth noting that the radio industry has lost about 14 percent of its advertising revenue, in real terms.

Table 2.4  
Radio Industry Advertising Revenues  
(\$ Billions)

Year	Revenue ( current \$)	Consumer Price Index	Revenue (2000 \$)
2000	19.85	172.2	19.85
2006	20.08	201.6	17.15
change	1.2%	17.1%	-13.6%

Source: Consumer Price Index, Bureau of Labor Statistics  
Advertising revenues, McCann Erickson Worldwide

### *Emergence of New Technologies*

Tables 2.5-2.8 describe prevailing patterns in the use of technologies having implications for both the music and radio industries.<sup>12</sup> Table 2.6 compares Internet use of 18-26 year olds with those of all adults. The younger “Generation Y” cohort is more

<sup>12</sup> These data were taken from *The Infinite Dial 2007: Radio’s Digital Platforms*, Arbitron/Edison Media Research, 2007.

likely to go online, listen to Internet radio or download music. In 2006, about 14 percent of persons surveyed reported that they downloaded music. Combined with information on total digital track downloads, this suggests that the average number of tracks (per person who downloaded) was 21. This is almost two albums worth of music per person. Since the average person purchases about two albums on an annual basis, this increase in Internet purchases could account for a large share of the music recording business.

Table 2.5  
Internet Use by Age and Total Adults, 2006

Activity	Age 18-26	All Adults
Go online	87%	72%
Use e-mail	98%	97%
Listen to Internet Radio	40%	26%
Download Music for fee	22%	12%
Download Music at no cost	32%	11%

Source: "Generation Y Adults Lead Internet Use, Lag in Television Use," *Research Alert*, EPM Communications, March 16, 2007.  
<http://rdsweb2.rdsinc.com/telex/rds/suite2>

Table 2.6  
Music Downloads, by Demographic

Age Group:	12-17	18-24	25-34	35-44	45-54	55-64	65+
% Report Downloads	24%	21%	20%	16%	10%	3%	1%

Source: *Internet and Multimedia 2006: On-Demand Media Explode*, Arbitron/Edison Media Research

Table 2.7  
Growth in Online Radio, 2000-2007

Date	Percent Listening to Online Radio
January 2000	2 %
January 2001	5%
January 2002	6%
January 2003	8%
January 2004	8%
January 2005	8%
January 2006	12%
January 2007	11%

*Source: The Infinite Dial 2007: Radio's Digital Platforms, Arbitron/Edison Media Research, 2007*

Table 2.8  
Ownership of Portable MP3 Players, by Age, 2005-2007

Age Group	January 2005	January 2006	January 2007
12-17	27%	42%	54%
18-24	18%	31%	39%
25-34	20%	30%	38%
35-44	16%	30%	38%
45-54	10%	16%	24%
55-64	6%	7%	14%
65+	2%	2%	6%

*Source: The Infinite Dial 2007: Radio's Digital Platforms, Arbitron/Edison Media Research, 2007*

Currently, about 12 percent of the population is listening to online radio. About one in three persons owns at least one portable MP3 player. This number has doubled in two years. In addition, there are significant differences by demographic group. Over half of all persons aged 12-17 have MP3 players. These percentages drop with the age of the group, falling to six percent for those aged 65 or older.

These surveys provide mixed evidence about the degree to which these technologies are complements or substitutes with each other.<sup>13</sup> While 16 percent of the respondents report purchasing music online, those who listen to Internet radio are twice as likely to do so.

#### *Radio Industry Facts*

Table 2.9 provides detailed information on radio industry operations for 2004. Two elements of these data are particularly germane to the issue of performance fees. Broadcast rights and license fees amounted to about \$869 million, representing about five percent of total industry revenues. Most of this total is from fees collected by

<sup>13</sup> The scholarly research on this topic is rather limited, though one study, Oberholzer and Strumpf (2004), present econometric evidence that downloading does not displace physical record sales.

performing rights organizations<sup>14</sup> on behalf of the music composers they represent.

Table 2.9  
Radio Industry Operations, 2004

Radio Industry Operations, 2004	Industry Totals, \$ Millions
Operating Revenue	\$16,494
Station time sales	\$12,803
Network compensation	\$93
National/Regional Ads	\$2,879
Local ad revenue	\$9,830
Network time sales	\$1,401
Program rights	\$258
Operating expenses	\$13,077
Annual payroll	\$5,100
Employee benefits	\$636
Contract labor	\$162
Materials and supplies	\$283
Purchased services	\$2,979
Data processing and computer	\$19
Communications services	\$175
Advertising and promotion	\$1,089
Electricity	\$135
Professional services	\$344
Lease and rental	\$408
Broadcast rights and license fees	\$869
Depreciation	\$1,010
Taxes and license fees	\$408
Other	\$1,630

Source: U.S. Census Bureau, "2004 Service Annual Survey, Information Sector Services"

Radio stations provide a variety of content formats, including music, news, talk, sports and other forms of entertainment (Table 2.10). Although stations can use a blend of programming, there are benefits to providing a consistent format. This practice promotes listener loyalty and audience demographics that are attractive to advertisers that wish to target specific market segments. Table 2.11 provides industry-wide, average quarter hour shares<sup>15</sup> for major format categories.<sup>16</sup> In 2006, nearly 80 percent of

<sup>14</sup> The bulk of domestic royalties are collected by two performing rights organizations, the American Society of Composers, Authors, and Publishers (ASCAP) and Broadcast Music, Inc. (BMI).

<sup>15</sup> Quarter-hour audience represents the numbers of persons aged 12 years or older who are listening for at least 5 minutes during a 15 minute period. The shares represent the percentages of the total audience.

listeners were tuned in to music format stations. News, talk, and sports formats were 17.6 percent. Some portion of the Spanish stations, about 25 percent, also had non-music formats.

Table 2.10  
Primary Radio Music Formats, BIA Financial Network and Arbitron

**Adult Contemporary**

80s Hits  
Adult Contemporary (AC)  
Hot AC  
Modern AC

**Album Oriented Rock/Classic Rock**

Active Rock  
Album Adult Alternative (AAA)  
Album Oriented Rock (AOR)  
Classic Rock

**Contemporary Hit Radio/Top 40**

Rhythmic Contemporary Hit Radio  
Pop Contemporary Hit Radio

**Country**

Classic Country  
Country  
New Country

**Jazz/New Age**

Jazz  
New AC (NAC)/Smooth Jazz

**Oldies**

Adult Hits  
Oldies  
Rock  
Alternative  
Classic Hits

**Spanish**

Latino Urban  
Mexican Regional  
Spanish Adult Hits  
Spanish Contemporary  
Spanish Oldies  
Spanish Tropical  
Spanish Variety  
Tejano

**Urban**

---

<sup>16</sup> Major format categories as defined by BIA Financial Network are listed in Table 2-11. The subcategories listed are the corresponding Arbitron definitions.

Rhythmic  
 Rhythmic AC  
 Rhythmic Oldies  
 Urban AC  
 Urban Contemporary  
 Urban Oldies

Of the music formats, Adult Contemporary had the most listeners, followed by Contemporary Hit Radio (also referred to as Top 40 or Pop), and the Urban format. Urban music includes Rap as well as Rhythm and Blues (R&B).

Table 2.11  
 Share of Radio Audiences, by Format

Format	1998	2002	2006	1998-2006
News/Talk/Sports	16.4	16.5	17.6	1.2
Adult Contemporary	15.7	14.7	14.8	-0.9
Spanish	6.7	8.4	11.2	4.5
Contemporary Hit Radio	10.7	12.1	10.7	0
Urban	8.2	9.1	10.1	1.9
Country	9.5	8.2	9.2	-0.3
Classic Rock	9.6	8.7	7.3	-2.3
Oldies	7.3	7.7	5.4	-1.9
Rock	4.9	5.0	3.4	-1.5
Religious	2.1	2.7	2.9	0.8
Jazz	3.0	3.1	2.6	-0.4
Classical	1.7	1.5	1.1	-0.6

Source: Arbitron, Fall Audience Surveys

Audience shares have changed over time, reflecting changing demographics as well as the impact of the technology changes described earlier. Of particular note are the increases in Urban and Spanish format audiences, as well as the declines in the Rock, Classic Rock and Oldies formats.

Age distributions are provided in Table 2.12. Nearly 40 percent of the youngest cohort of 12-17 year olds listen to Top 40 or Contemporary Hit Radio. Very few of these younger audiences listen to non-music formats. Slightly older audiences shift towards Adult Contemporary. Baby boomers listen to Adult Contemporary but there is also a pronounced shift to Classic Rock and Oldies. Country music also has an older demographic. For the oldest demographics, stations with non-music formats are the most popular.

Table 2.12  
Radio Format Share of Audience By Age

Format	Age 12 -17	Age 18 - 24	Age 25 - 34	Age 35 - 44	Age 45 - 54	Age 55 - 64	Age 65 +
News/Talk/Sports	3.9%	5.3%	10.4%	17.4%	22.5%	29.1%	32.7%
Country	10.7%	13.7%	13.7%	14.1%	15.0%	18.2%	22.5%
Adult Cont./Hot Adult/Adult Hits	8.3%	10.8%	15.3%	18.2%	17.0%	14.9%	12.5%
Pop/Rhythmic Contemporary	39.8%	25.9%	16.4%	8.5%	4.2%	2.2%	1.4%
Classic/Album Oriented Rock	5.1%	8.4%	9.1%	11.8%	10.8%	4.3%	1.2%
Oldies/Classic Hits	2.1%	3.2%	3.1%	5.2%	10.5%	12.1%	7.3%
Urban Contemporary	12.9%	9.7%	7.2%	4.1%	2.4%	1.6%	1.3%
Alternative/Active Rock	7.8%	10.5%	8.6%	5.0%	2.2%	0.7%	0.4%
Urban Adult Contemporary	2.4%	2.6%	3.8%	5.1%	5.2%	4.7%	3.2%
Mexican Regional Contemporary	2.7%	6.8%	7.4%	3.7%	2.0%	1.7%	1.4%
Christian	3.5%	2.0%	3.3%	3.9%	3.3%	2.1%	1.4%
Classical	0.5%	0.5%	0.9%	1.2%	2.0%	4.5%	10.4%
Jazz/Smooth Jazz	0.5%	0.5%	0.9%	2.0%	2.9%	4.0%	4.2%

Source: Arbitron, 2006

Table 2.13 provides additional information about the 2006 playlists of a sample of radio stations. Frequency of play was compiled from a sample of stations and includes the total number of spins by track.<sup>17</sup> All tracks that had at least five spins were included. The table provides the average number of total spins for the complete sample of tracks. The average number of spins per track is also computed. The same numbers were computed for the top 10 tracks during that year. For an average Top 40 station, over 90,000 spins were recorded for a total of 273 tracks. This represents about 342 spins per track. In other words, a track would be played an average of nearly one time daily over

<sup>17</sup> Data were provided by MediaBase, an organization that monitors playlists. Stations located in New York, Los Angeles, and Chicago were included in the analysis.



the full calendar year. This number understates, to some degree, the frequency with which a Top 40 track is played over a shorter period of time. This is because some tracks get play time at the end or beginning of a calendar year and their total exposure is not included in the 2006 summary. In addition, the “life” of most hits is considerably shorter than a year. For all but the “hottest” of the Top 40 hits, their appearance on playlists lasts only a few months.

In contrast, the top 10 hits of the year average more than five times the exposure of the “average” hit. These mega hits received an average of 1,761 spins during 2006. That amounts to about five plays per average day. If most of these are concentrated during a six-month period, it is possible that a song is played every other hour in at least one station in the market. Recall that an average person may spend two hours listening to the radio on a daily basis. This suggests that a person might well hear a particular track virtually every day.

Table 2.13  
Distribution of Playtime for Top Radio Tracks, 2006

	Total Spins	Total Tracks	Spins/Track	Top 10 Tracks	Spins/Track
Top 40	93,423	273	342	17,613	1,761
Rock	47,448	324	146	9,986	999
Classic Rock	60,515	1,900	32	1,884	188
Hot AC	53,680	126	426	13,302	1,330
Alternative	39,057	488	80	5,050	505

Source: MediaBase playlist data for leading stations in Los Angeles, New York, and Chicago. Lists include all tracks with at least 5 spins.

For the format called Hot Adult Contemporary, the pattern is similar. However, for other music formats, such as Rock, Classic Rock, and Alternative, the playlists are more diverse and the intensity of play for any one track is much more modest. Classic Rock stations averaged 1,900 tracks with at least five spins during the year. These tracks were aired about one time per month. Even the most popular tracks would be aired only once every other day.

With the changes in FCC ownership restrictions, multiple-ownership in the radio industry increased over this time period. Although some observers believe that consolidation reduces media diversity, there exist theoretical reasons to suspect that this may not be the case.<sup>18</sup> The intuition for this is straightforward. If a single owner owns two stations in the same market, it has an incentive to maximize *total* audience rather than the audience of individual stations. Thus, it will not program in ways that promote competition for the same audience. Indeed, an examination of the playlists for the same kinds of stations described in Table 2.13 indicated virtually identical patterns of play time in earlier years. Although this sample was small,<sup>19</sup> there was no evidence of changes in the variety of music made available by this group of stations.

### *Trends in the Music Recording Industry*

As has been well-documented elsewhere,<sup>20</sup> the last decade has been a turbulent period for the music industry. Beginning with Napster and the associated onslaught of unauthorized downloading,<sup>21</sup> there has been a steady erosion of industry revenues. Although legal and regulatory mechanisms have emerged to slow the losses, the industry still faces significant risks. Digital technologies, alternative distribution channels, changes in consumer behavior and a reduction in market entry barriers all threaten the dominance of the major record labels.<sup>22</sup>

Industry sales trends for physical unit formats are presented in Table 2.14. From 2000 through 2003, sales of CDs fell by an average rate of about six percent annually. On the surface, it seems likely that these declines were a direct result of illegal

---

<sup>18</sup> Using modeling approaches first introduced by Steiner (1952), Owen and Wildman (1992) demonstrate that, under plausible conditions, local consolidation could result in more, not less diversity. Sweeting (2006) develops a sophisticated measure of programming diversity (measured as vector differences between radio playlists) and finds that local concentration increases variety of programming.

<sup>19</sup> The sample analyzed consisted primarily of stations acquired by large radio groups during the last 6 years.

<sup>20</sup> For a thorough overview of the music industry, see Krasilovsky and Shemel (2007).

<sup>21</sup> Mortimer and Sorenson (2005) cite data indicating that Napster had 20 million accounts at the peak and over half a million connections at any given time.

<sup>22</sup> According to sales data compiled by Nielsen SoundScan and reported in Krasilovsky and Schemel (2007), the four dominant labels, Universal, Warner, Sony BMG, and EMI, controlled 31, 15, 25, and 10 percent of the market respectively during the first three quarters of 2005, for a total of 81 percent. This is in stark contrast to Census of Manufacturers data referenced in Dertouzos and Wildman (1979) indicating that the four largest companies controlled 48 percent of industry sales.

downloading.<sup>23</sup> Despite experiencing a modest recovery in 2004, the downward trend continued in 2005 with a drop in unit sales of eight percent, and in 2006 with a drop of 13 percent.

Table 2.14  
Music Industry Sales, Physical Units 2000-2006

Physical Units:	2000	2001	2002	2003	2004	2005	2006
CDs	942.5	881.9	803.3	746.0	767.0	705.4	614.9
Music Video	18.2	17.7	14.7	19.9	32.8	33.8	23.1
Other (albums)	78.2	47.6	33.3	20.5	7.7	4.4	1.7
Other (singles)	40.3	21.3	8.4	12.1	6.6	5.0	2.9
Dollar Value:	\$12,705	\$12,389	\$11,549	\$11,053	\$11,423	\$10,478	\$9,053

Source: Recording Industry Association of America

The distribution of 2006 album sales for the Los Angeles market is presented in Figure 2.1 and Table 2.15. The top seller in the Los Angeles market area, Gnarl's Barkley's *Crazy*, sold over 120,000 copies. However, the individual unit sales fall dramatically as one moves down the rank order. The top 10 albums averaged about 93,000 sales each, accounting for almost eight percent of total sales. The top 100 sold over 4.5 million copies, an average of just over 45,000 copies. These titles, representing 10 percent of the 1,000 albums considered, accounted for nearly 37 percent of market sales. These distributions roughly correspond with those based on radio play time. Even the most popular music represents only a small share of either music exposure or retail album sales.

<sup>23</sup> It is noteworthy, however, that most academic studies of this issue are inconclusive. See, for example, Rob and Waldfogel (2006)

Figure 2.1  
2006 Distribution of Album Sales, Los Angeles DMA

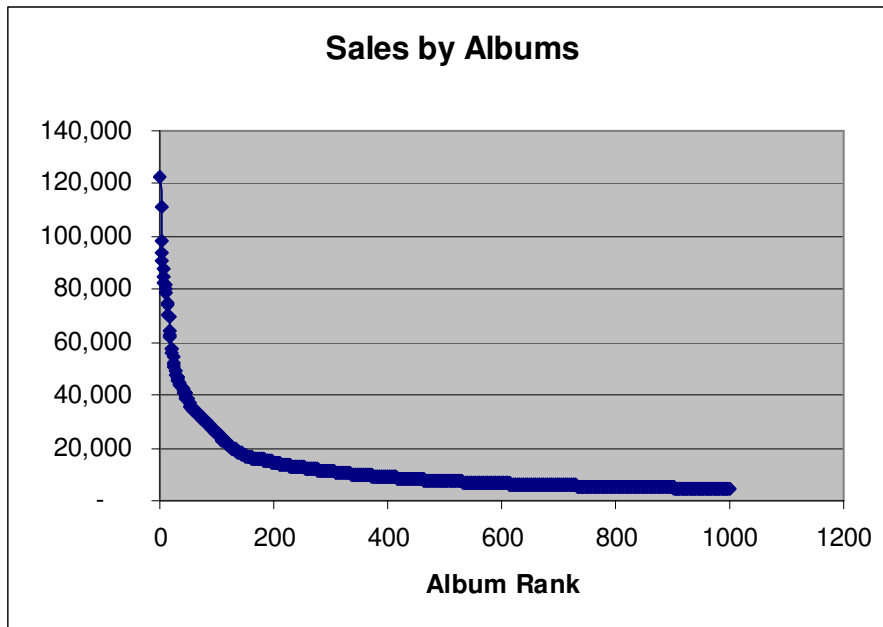


Table 2.15  
Concentration of Album Sales, Los Angeles DMA, 2006

	Total Unit Sales	Percent of Top 1000
Top 1000 Album Sales	12,307,924	100%
Top 100 Album Sales	4,536,607	36.8%
Top 10 Album Sales	934,481	7.6%

Source: Nielsen SoundScan

It is revealing that, over the same time period, digital downloads increased dramatically. These data are displayed in Table 2.16. As a legal method of distribution, this market was virtually nonexistent in 2003, but sales rose rapidly over the three-year period, and unit sales of singles approached 600 million by 2006. In comparison to the decline in CD sales, the revenue implications of digital downloads are modest. The two billion dollar decline in CD sales is not offset by the \$878 million in digital track revenues in 2006.

Table 2.16  
Music Industry Sales, Digital Downloads, 2004-2006

Digital Units:	2004	2005	2006
Download single	139.4	366.9	586.4
Download album	4.6	13.6	27.6
Mobile (master ring tunes, etc.)		170.0	315.3
Subscription		1.3	1.7
Dollar Value:	\$183	\$504	\$878

Source: Recording Industry Association of America

However, this is misleading because the profit margins generated by digital sales are larger than those associated with physical CD sales.<sup>24</sup> Digital distribution is relatively inexpensive, amounting to about 17 cents per track. In contrast, CDs involve a 75 cent packaging and \$2 distribution cost. Further, retail mark-ups are about \$5. On a per track basis, these costs add up to about 65 cents. CDs generate about \$1.25 in revenue per track, and about 25 cents in profit. With cost savings of about 50 cents per track, it is easy to conclude that potential revenue from paid digital downloading bodes well for the future of the recording industry.

The distribution of music sales by age group is provided in Table 2.17. The changes reflect demographic trends, namely the aging of the baby boom cohort, resulting in larger populations aged 45 and above. In addition, the reduced and delayed fertility of that generation have resulted in smaller numbers representing the younger ages.

Table 2.17  
Distribution of Music Sales by Demographic

Age:	1990	1995	2000	2005
10 to 14 yrs.	7.6%	8.0%	8.9%	8.6%
15 to 19 yrs.	18.3%	17.1%	12.9%	11.9%
20 to 24 yrs.	16.5%	15.3%	12.5%	12.7%
25 to 29 yrs.	14.6%	12.3%	10.6%	12.1%
30 to 34 yrs.	13.2%	12.1%	9.8%	11.3%
35 to 39 yrs.	10.2%	10.8%	10.6%	8.8%
40 to 44 yrs.	7.8%	7.5%	9.6%	9.2%
45 yrs. +	11.1%	16.1%	23.8%	25.5%

Source: Recording Industry Association of America

<sup>24</sup> Cost data are reported in Anderson (2004)

That said, it remains the case that the younger cohorts purchase more than a proportionate share of music sold. For example, the population aged 45 years or older represents 36 percent of the population but 25.5 percent of sales. The 15 to 34 year-old group represents 32 percent of the population, but 48 percent of sales. This suggests that per capita music sales are more than double for the younger groups. This difference is similar to the age-specific accounting of the time spent listening to music either on the radio or recorded music. These patterns have held up over time, suggesting that new technologies appear to supplement rather than substitute for consumption of traditional media.

In addition to the increase in digital track downloads, other changes have occurred in the distribution of recorded music. Table 2.18 summarizes sales revenues by retail outlet. In 1990, specialty record stores dominated distribution, with 70 percent of all sales. In the decade that followed, sales shifted away from record stores, with the largest increase occurring in “Big Box” retail chains such as Wal-Mart. While such outlets could have as many as 40,000 titles in stock, inventory restrictions created barriers to entry for small independent labels or artists who were not well established. With the expanding role of the Internet, there are no longer physical constraints on inventory. Indeed, the largest online service, Rhapsody claims to have over 4 million available titles.<sup>25</sup> This creates new opportunities for innovative artists and smaller independent labels to succeed in the competitive marketplace.

Table 2.18  
Distribution of Music Industry Revenues by Retail Outlet

Outlet:	1990	1995	2000	2005
Record store	69.8%	52.0%	42.4%	39.4%
Other store	18.5%	28.2%	40.8%	32.0%
Tape/record club	8.9%	14.3%	7.6%	8.5%
Ad or 800 number	2.5%	0.4%	2.4%	2.4%
Internet			3.2%	8.2%
Digital download				6.0%

Source: Recording Industry Association of America

<sup>25</sup> This statistic is found at [www.rhapsody-signup.com](http://www.rhapsody-signup.com).

### ***3. Previous Evidence on the Sales Impact of Radio Exposure***

The conventional wisdom is that radio play stimulates record sales.<sup>26</sup> This belief is certainly consistent with the anecdotal evidence, including the fact that record companies pay large sums to promote their releases. In addition, surveys of consumers indicate that the exposure to radio is a primary method of learning about music. Unfortunately, there has been little scholarly research on this topic.<sup>27</sup> In this section, we begin with a brief discussion of available survey evidence and review some of the more recent contributions to the literature.

#### *The Anecdotal and Survey Evidence*

Judging from the behavior of record companies, radio play is essential to the success of a new album. It is believed that radio campaigns through independent record promoters cost from \$500 to \$2,000 each time a station adds a song to a playlist for a single week.<sup>28</sup> Taking the average of \$1,250 and applying it to the typical Top 40 station in an average market, this comes out to nearly one-fifth of a penny per exposure (an exposure is equal to one listener listening one time).<sup>29</sup>

Consumer surveys suggest that these dollars are well spent. For example, a survey of rock music buyers found that over 80 percent of albums were purchased

---

<sup>26</sup> As Bard and Kurlantzick (1974), p. 95 noted: "It is an accepted fact that radio play stimulates record sales by exposing new releases to potential buyers; in other words, radio play advertises records."

<sup>27</sup> As Sidak and Kronemyer (1987) observe "There appears to be no published study confirming this complementary demand relationship, let alone estimating its empirical magnitude." On the other hand, there exists a larger base of research examining the impact of file sharing and illegal downloading on record sales. These efforts face the same technical challenges that burden studies of the impact of radio play. However, they are also hampered by the absence of reliable data on file sharing or illegal downloading. One of the more creative attempts to estimate the impact of digital downloading can be found in Robb and Waldfogel (2006). Their analysis utilizes data on individual college students and takes advantage of contrasting university Internet access policies that provide exogenous variation in the volume of downloading. Still, despite these best efforts, the resulting evidence is very mixed and sensitive to alternative approaches and assumptions.

<sup>28</sup> See the discussions in Krasilovsky and Shemel (2007) and Bryan Farrish Radio Promotion, December 11, 2005 (<http://www.radio-media.com/>).

<sup>29</sup> With average quarter hour ratings of .7 percent and an average audience of 16,100 listeners (.007\*2.3 million), the typical Top 40 track gets no more than 42 spins in a week, which equals about 676,000 exposures (or gross rating points). Per exposure, this amounts to \$1,250/676,000 or .0018 dollars per exposure, or nearly one-fifth of a penny. These calculations can not be viewed as precise but they certainly suggest that the promotional value is significant.

because a particular track was first heard over the radio.<sup>30</sup> Today, about half of those surveyed claim to be influenced by radio in making their music purchase choices.<sup>31</sup>

Table 3.1  
Percent of Respondents Relying on Media Sources for Information about New Music

Year	Internet	Newspapers	Radio	Television
2002	9%	2%	63%	14%
2007	25%	4%	48%	12%

Source: Arbitron Inc./Edison Media Research Survey of 12+ Population, 2007.

#### *Recent Econometric Contributions*

There have been two recent contributions to the literature on the relationship between radio airplay and album sales. The first, by Montgomery and Moe (2002), examines the empirical relationships between weekly sales volumes for a sample of new album releases and radio airplay of those tracks. The results of this study are consistent with conventional wisdom, survey data and industry practices. In particular, they find that sales of individual albums are promoted by radio play. A second, more recent study, by Liebowitz (2007), examines aggregate sales of albums in the top 100 designated market areas (DMAs). He examines the changes between 1998 and 2003 in album sales and estimates the impact of changes in Arbitron ratings for stations with music formats. In contrast to the Montgomery and Moe findings, Liebowitz finds a large *negative* effect on an industry level.

#### *Econometric Challenges to Establishing a Relationship between Radio Play and Sales*

In establishing the empirical relationship of interest, several technical obstacles must be overcome. These include measuring radio exposure, filling in data that are not available, allocating data to a common geographic unit, eliminating spurious correlations, and choosing the correct functional form.

<sup>30</sup> Rein (1972).

<sup>31</sup> The fact that fewer individuals claim that they are influenced by radio does not necessarily imply that recording companies or artist would value airplay any less. As noted in the advertising literature, audience fragmentation might require higher expenditures in order to achieve the requisite frequency and reach. This is the logic that explains the increase in television advertising rates that have occurred even as prime time audiences have decreased. For a discussion, see Dertouzos and Garber (2003)



### 1. Measuring Radio Exposure

The first challenge is to construct an appropriate measure of exposure to music. Traditionally, the degree to which a radio advertisement penetrates a market is represented by reach (the number of listeners hearing a given ad) times frequency (the number of times the ad is heard). Analogously, the average exposure to music can be expressed as ratings times the number of spins. One spin is a single airing of a music track or song. Thus, data must be gathered on radio audiences, as well the amount of music to which these audiences are exposed. The Montgomery and Moe analysis utilizes information on both ratings and spins, whereas Liebowitz does not. Therefore, the information used by Montgomery and Moe is superior to the information used by Liebowitz.

### 2. Filling in Unavailable Data

Station audience ratings are available through Arbitron, and the volume of music played is measured by a number of organizations including Nielsen BDS, Mediaguide and Mediabase. Ratings are available for radio stations that meet Arbitron's minimum reporting standards, although not all of these are monitored for airplay, and a study's estimation methodology should account for this. Both the Montgomery and Moe and the Liebowitz studies are flawed in that they do not adjust for this issue. Since Montgomery and Moe are examining aggregate ratings over shorter time intervals, the extent to which data are unavailable is unlikely to change and is therefore less problematic. For the Liebowitz study, which looks at DMA-level changes over a five-year period, the data errors are more problematic.

### 3. Data Allocation to a Common Geographic Unit

Any analysis must rely on data gathered from multiple organizations that have different data perspectives, primarily because of whom they serve. For example, Nielsen data, including the Nielsen SoundScan music sales data and Nielsen BDS play data, were only available for DMA areas, which is how television markets are defined. Arbitron data initially is defined at the metro market level, and BIA Financial Network information for radio stations can be acquired at the metro market level. Metro markets do not correspond to DMAs, but Arbitron does make its data available at the DMA level. Much of the relevant U.S. Census and Bureau of Labor Statistics data are provided for

geographic units that are consistent with the levels of public sector governance, namely counties, Metropolitan Statistical Areas (MSAs) and states. These areas do not always correspond with the metro markets or DMAs. Thus, a major challenge is to organize data into relevant geographic units in a manner that reflects true levels of both the outcome variables of interest and factors thought to explain them.

Since the Montgomery and Moe piece utilizes national data, such allocation issues are not relevant. For Liebowitz, who constructed his DMA-level information based on examining Nielsen DMA maps (rather than using Arbitron's data at the DMA level, for example) and in this way matched metropolitan areas that do not correspond with the same geographic boundaries, this presents a significant problem. This issue is even more problematic given the changes in the relative growth and/or significance of this discrepancy over the five-year period. For example, if there is more population growth in the non-MSA portion of a DMA over this time period, then trying to link music sale *changes* in a DMA with those in a subset of the larger market is unlikely to yield reliable estimates.

In fact, the Liebowitz allocation method seems ad hoc and is not described sufficiently. For example, it is not clear that he dealt with the problem of audience overflow, that is, the fact that nearly half of the radio stations have audiences in multiple DMAs. It seems, although this is not clear from the descriptions, that ratings information for a station was allocated in its entirety to a single DMA based on eyeballing coverage areas as they appeared on a map. Also, Liebowitz does not account for population and/or audience distributions across DMAs or station coverage areas.<sup>32</sup>

#### 4. Distinguishing Causation from Spurious Correlation

The goal of these analyses is to establish a causal relationship between radio music exposure and sales of recorded music. This requires a well-specified and

---

<sup>32</sup> It is also impossible to tell which Arbitron ratings Liebowitz relied on. It is described simply as "Time Spent Listening." This measure seems similar in value to the one obtained by converting average quarter hour ratings (which actually only reflect a five-minute block of listening within quarter hour segments) to total time. However, the variable published by Arbitron and labeled TSL (time spent listening) relates to the average time spent in a day by an average listener. To the extent that stations (even when they have the same ratings) have different numbers of unique or cumulative listeners, it is not clear how one would add these up across stations to get a reliable measure of audience exposure. For the work reported below, we identified audience numbers in a particular quarter hour, allocated them to the appropriate DMA (or group of DMAs) and then summed them.

comprehensive econometric model that accounts for both observed and unobserved factors that can simultaneously affect both music exposure and retail sales. If this is not accomplished, there is the danger that an artificial correlation having nothing to do with causation may exist.

The Montgomery and Moe research faces a challenge in this regard because the week-to-week relationship between sales and radio airplay for individual albums is likely to be confounded by a simultaneous determination process. The authors recognize that causation may go in two directions and therefore use vector autoregressive models (VARMA) designed to isolate cause and effect.

Although reverse causality is somewhat less of an issue at the aggregate DMA level, there remains a concern that unobserved factors could well affect the levels of sales and radio airplay simultaneously. Under the assumption that such factors are constant over time, Liebowitz argues that differencing (that is, examining changes instead of levels between the two time periods) will net out any unobserved influences that are DMA-specific and fixed over time. However, this is a very strong assumption and is likely not to hold true over a five-year period. The problem is likely to be compounded by other issues created by audience measurement challenges such as unavailable station data and the need to reallocate data to different geographic areas.

Further, the differencing approach he utilizes nets out many of the variables of interest and further reduces efficiency of the estimation process. In Appendix A, we explore the relative merits of alternative econometric approaches and conclude that differencing is an inferior approach under the wide range of conditions likely to prevail in these circumstances.

##### 5. Specifying the Correct Functional Form

In most econometric studies, findings can be quite sensitive to alternative assumptions about the relationships between variables of interest. For example, is the impact of music performance linear with increases in radio play? Does the relationship have a traditional promotional “S-Curve shape,” whereby exposure to music needs to pass a minimum threshold of exposures to have an effect?

The Montgomery and Moe formulation is flexible enough to allow for non-linear relationships and finds that, on average, the impact of an increase in radio play is greater

than the impact of reducing radio play. Consistent with the existence of an S-Curve, this suggests that radio play is more effective once one gets beyond a certain threshold of exposure.

The Leibowitz results are dubious because of some unfounded assumptions about the pattern of regression errors. In particular, he assumes that regression errors are larger for the small DMAs based on the observation that radio markets and DMAs are a better match for large markets. While this is often true, it is not uniformly the case. And, more importantly, there are other sources of error that could have quite different patterns, especially since he is examining changes, not levels, in the variables. It would have been more appropriate to analyze the actual patterns of regression error and once identified, take appropriate steps to overcome them.<sup>33</sup> This is not a minor issue, because the weighting scheme utilized places virtually all the emphasis on the few largest DMAs. Thus, they end up driving the estimated relationships. This would not be so much a problem except for the fact that the key result of interest – the estimated effect of radio play on sales – is not significant otherwise. In fact, a number of reasonable – even preferred – approaches reported by Liebowitz fail to provide significant results. Unweighted regressions, using levels rather than differences, and using an instrumental variable approach (to deal with possible simultaneity problems) are all reported. None of these approaches yields a significant effect. Indeed, even in cases where the coefficient is negative, the imprecision as reflected in large standard errors makes it impossible to reject the distinct possibility that the true effect is actually positive. Simply put, you cannot draw sufficient conclusions from these regressions. This is because the estimated coefficients in some specifications are not significantly different from any value within a full range of theoretically plausible effects.

In addition, the time period being analyzed was one of rapid change and was also quite unique in that music purchases were plummeting at the same time that illegal downloading was rampant. Although Liebowitz includes a variable (the level of Internet penetration) as a proxy for this activity, it is unlikely that it represents an accurate control. Indeed, in earlier research, Liebowitz highlights this problem and argues that the

---

<sup>33</sup> For example, in the econometric analysis reported below, simple heteroscedasticity tests (regressing the size of the residual on a set of covariates) indicates that no weighting of observations is appropriate.

post-Napster period, 2004 and beyond, would be a “better period” for conducting an analysis.<sup>34</sup>

For these reasons, the Montgomery and Moe paper must be considered more reliable. Its findings for 13 album releases by Capitol Records during the mid-1990s indicate that airplay can have a significant promotional effect. The results suggest that a 30 percent decline in air time would result in a 16 percent decline in record sales, implying an elasticity of over .50. Put another way, even if record labels were willing to pay the full advertising spot rate for the time used to play their music, the promotional value would be far in excess of the cost.

That said, the Montgomery and Moe paper cannot be considered definitive. The period of time (early to mid-1990s) was quite different than it is today. We have argued that the implications of subsequent changes for the value of radio play are not all that obvious. Still, the issue should be analyzed using more current information. Perhaps more importantly, the study examined only 13 album releases, representing only top 40 music and a small share of the genre at that. Although we have argued that the promotional effects for individual albums (or at most groups of albums) is the relevant information for estimating values to reflect real market outcomes, the effects for this small subgroup may not reflect music recordings more generally. Thus, additional evidence would be valuable. To this new research we now turn.

---

<sup>34</sup> See Liebowitz (2005).

#### ***4. An Econometric Analysis of Radio Airplay and Recording Sales***

This section describes our empirical study of the relationship between radio play and sales of recorded music. The objective of this study was to quantify the relationship between radio airplay and the sales of albums and digital tracks from 2004 to 2006 in the 99 largest designated market areas (DMAs).<sup>35</sup> An econometric approach was used to link sales with variations in music exposures, while controlling for a variety of other local market factors, including demographic and economic characteristics. The measure shown in previous research to be the most appropriate measure for music exposure was used to calculate economic impact, that is, the number of listeners multiplied by the number of “spins” or plays of a music track.

Results showed the estimated impact of radio exposure was positive and significant for all audience measures. In addition, the results were remarkably insensitive to alternative assumptions about functional relationships and econometric methods.

##### *Methodological Challenges*

As mentioned in Section 3, two methodological challenges faced by researchers who have conducted previous studies were addressed in this study. First, music exposure data are not available for all radio stations. Second, observed sales as well as radio exposure could be influenced by factors that cannot be adequately accounted for by looking at just sales and radio exposures. Thus, additional market and consumer information should be considered.

For a subset of small stations, information on spins is not available. In other instances, ratings data do not meet Arbitron standards for statistical reliability. Since information is typically unavailable only for the smaller stations in a market, it is possible that the total sum of music exposures provided by the largest stations represents an accurate *relative* index for making market-to-market comparisons. However, it is also possible that markets vary significantly in the degree to which data are available. If this

---

<sup>35</sup> Nielsen SoundScan provides data for the largest 99 DMAs as well as a “blended” DMA based on all others not in the top 99. In this analysis, we excluded the blended DMA since it consists of over 100 separate markets that are geographically dispersed across the entire United States.

is true, the use of incomplete data could confound the observed relationship between music recording sales and radio exposure. This could bias the data, and possibly does bias results reported in previous studies.

To address this potential for bias, estimates of radio music exposures were constructed here using standard data imputation techniques. Based on observed correlations between music exposures and a full set of local market and radio station characteristics, estimates were constructed for the subset of stations for which there was no information. These estimates were then summed and added to the actual DMA-level information for the other stations with complete information.<sup>36</sup>

The second potential issue could arise due to a spurious correlation between music sales and radio exposure. One cause of this correlation could occur if there are unobserved factors, such as taste for music, that affect both sales and music exposures simultaneously. For example, imagine that residents of the Boston DMA are more likely to be sports fanatics. As a result, they spend less time listening to music, whether on the radio or from purchased recordings. Thus, radio exposures are lower as are music sales. However, these reductions do not imply a cause and effect. Instead, they are both lower due to an unobserved third factor, namely the taste for an alternative form of entertainment--sports.

To address this challenge, there are standard methodologies, called “instrumental variable” or “simultaneous variable” techniques. In a nutshell, these methods involve generating predictions for music exposures based on true relationships between actual exposures and a set of observed factors. Based on these true relationships, predictions were generated for each station. These predictions proved to be accurate. The predictions were not influenced by the aforementioned “unobserved” factors. So, the estimated relationships between predicted radio exposures and music sales had been purged of any spurious correlations.

## 1. Measuring Radio Exposure

---

<sup>36</sup> The listening audiences of most radio stations are mostly confined to the home DMA. However, radio signals frequently spill over into contiguous markets, resulting in music exposures across multiple DMAs. Although such spillovers represent a small portion of DMA audiences, the most precise DMA exposure measures should account for the actual location of listeners. To account for this, Arbitron audience information was allocated to specific DMAs.

As discussed earlier, the appropriate measure of advertising penetration is given by both reach and frequency. In the case of music exposure, this can be expressed as the listening audience times the number of spins. Information was obtained on ratings as well as airplay time.

## 2. Filling in Unavailable Station Data

Station audience ratings were available through Arbitron and the volume of music played was provided by Nielsen BDS and Mediaguide.<sup>37</sup> Table 4.1 reports the number of station-year combinations listed by BIA Financial Network as having the following music formats during the 2004, 2005 and 2006 calendar years: Adult Contemporary, Classic Rock, Oldies, Country, Jazz/New Age, Top 40, Spanish and Urban. Of the nearly 22,000 observations (over 7,000 stations in the sample for three years each), only about half had audience ratings. Music spins were provided for less than 20 percent of the sample.

Table 4.1  
Frequency of Exposure Measures by Station Observations 2004-2006

Number of station observations, BIA Financial Network	21,922
Stations-years with Arbitron ratings	11,150
Music spins, Nielsen BDS	3,077
Music spins, Mediaguide (MG)	4,650

As demonstrated later in this section, the likelihood of being included in the Arbitron, Nielsen BDS or Mediaguide samples increases dramatically with the size of the station. We decided that these larger stations account for a significant portion of total radio audiences. However, we felt that data gaps remained potentially problematic, especially if the extent of unavailable information was correlated with other factors, such as market size. Thus, we decided that it was necessary to implement several empirical strategies, outlined below, to “fill in” or otherwise account for unavailable data. This care had not been taken for previous research on this topic.

<sup>37</sup> A subset of radio stations do not meet Arbitron minimum reporting standards. Meeting Arbitron’s minimum reporting standards requires that a station have: (1) at least five minutes of listening within a quarter-hour in 10 Metro diaries and (2) a .495 Metro Cume rating, and (3) a .05 Metro Average Quarter-Hour (AQR) rating.



### 3. Data Allocation to a Common Geographic Unit

For completeness, this study relied on information gathered from multiple organizations that provide data for incompatible geographic units. Nielsen data, including the Nielsen SoundScan music sales data and Nielsen BDS play data, were available at the DMA level. Arbitron data, as well as the BIA Financial Network information on radio station and local markets, were provided for radio markets as well as DMAs. Market data were gathered from government sources such as U.S. Census and Bureau of Labor Statistics. These data were only provided for counties, Metropolitan Statistical Areas (MSAs) and states.

As indicated, the key outcome measures, albums and digital tracks sold were provided at the DMA level. Since this represents the highest level of geographic aggregation, the DMA is the unit of analysis that makes the most sense. Unfortunately, the mapping of information from radio markets and MSAs into DMAs can not be accomplished in a straightforward manner. To deal with this, two strategies were employed. First, demographic and economic data were gathered primarily at the county level. Although not perfect, the cross-walks between counties and DMAs are quite precise. Lastly, radio station information was allocated on the basis of listening audience distribution across DMAs, which was available for all rated stations (through Arbitron). For stations where such information was not available, alternative assumptions were made and sensitivity tests conducted.<sup>38</sup>

### 4. Distinguishing Causation from Spurious Correlation

The goal of this analysis is to establish a causal relationship between radio music exposure and sales of recorded music. The methodology should account for both observed and unobserved factors that will simultaneously affect both music exposure and retail sales. If this is not done, then one observes an artificial correlation having nothing

---

<sup>38</sup> In particular, stations without Arbitron information are much more likely to be stations with smaller, geographically confined audiences. Thus, the assumption that the distribution across DMAs would be the same for the stations with unavailable data probably understates the allocation to the home DMA. An alternative approach was to assume that all of the imputed audience and music exposure is local. Since these alternative methods can be viewed as extreme assumptions, the two sets of results serve to bound the possible error. As we will see, the results were not very sensitive to the approach taken, so this issue is, for all practical purposes, a nonissue.

to do with causation. For example, imagine that individuals in the South like Country music and audiences in the Northeast prefer news or sports formats. Not surprisingly, more stations will play Country music in the South while non-music formats will be more frequent in the Northeast. It would not be surprising to find that album sales will also be higher in the southern markets, not necessarily because of the radio exposure, but because local tastes increase music consumption across the board.

Spurious correlations could be negative as well. For example, imagine that low income levels promote radio listening (which is free) while discouraging the purchase of more expensive audio equipment such as computers, iPods and CDs. Without adequately controlling for such plausible income effects, the raw correlation between radio listening and music purchases could be negative.

A well-specified model that controls for most of the key factors limits the risk of such spurious correlations. Some unobserved factors not accounted for always will be observed. To address this, one can utilize simultaneous equation methods that can purge the data of the influence of these unobserved factors. By estimating a model that links radio play with exogenous factors that are observable, one can then utilize the predictions based on this model. Because the predictions will be based only on factors in the model and not on the factors excluded, the causal relationship will no longer be confounded.

#### 5. Choosing the “Correct” Functional Form

Although the “S-Curve” has some intuitive appeal, the shape of the “true” relationship between music sales and airplay is impossible to establish *ex ante*. In this research, the choices will be guided by the evidence. That is, do the models explain the patterns in the data? Which specifications do a better job? And how sensitive are the key results to alternative assumptions?

#### *Data Sources*

Information for this study was derived from a variety of sources. Radio station characteristics and coverage area data were provided by BIA Financial Network. Ratings data for radio metro markets (average quarter hour audiences) were taken from Arbitron MaximiSer for spring and fall for the years 2004, 2005 and 2006. Radio ratings at the

DMA market level were also taken from Act 1 Systems software.<sup>39</sup> Digital track downloads and album sales by broad genre categories were obtained from Nielsen SoundScan for the 99 largest DMAs. Annual music playtime, or track spins, for a subset of stations, was obtained from Nielsen BDS. Supplemental spin information was provided by Mediaguide for spring and fall of 2004-2006.

Additional demographic information, describing the demographic and economic characteristics of both the radio metro markets and DMAs, was gathered from the Bureau of the Census, the Current Population Survey, the Bureau of Labor Statistics, BIA Financial Network and Arbitron.

*The Radio Station Data Base*

Table 4.2 describes the primary radio station sample. All stations identified in the BIA Financial Network database as being educational, low power, “dark,” or non-commercial were excluded. Format categories included Adult Contemporary, Classic Rock, Country, Jazz/New Age, Oldies, Rock, Spanish, Top 40, and Urban.<sup>40</sup> In the logistic analysis reported below, Ethnic, Religious, Classical and all other music formats were also included. Since the focus of this study is the influence of radio play on music sales, non-music formats were excluded. Accordingly, stations reporting news, sports, or talk formats were not analyzed.

For each station, a dummy variable was constructed for the class of station, A through D. These designations are based on signal strength as well as spectrum location.

---

<sup>39</sup> Act 1 Systems software makes Arbitron summary data sets available at the DMA level and also allows multimarket analyses.

<sup>40</sup> Format categories were reported by BIA Financial Network as well as by Arbitron. The correlations between these data were quite high, though imperfect. The main advantage to the Arbitron information was the finer distinction between Spanish categories such as Spanish “Talk” and Spanish “Adult Contemporary.” On the other hand, the Arbitron formats were only available for the subset (about 50%) of BIA Financial Network stations. Since a key part of the estimation was to account for the influence of those stations that were not rated, the BIA Financial Network format data were more useful. In cases (< 1%) where there was no BIA Financial Network information, the Arbitron formats were utilized.

Table 4.2  
Station Data Set

Variable	Mean	Standard Deviation
Exposure Variables:		
Arbitron audience	4,654	9,216
log(Arbitron audience)	7.5490	1.3482
exposures, Nielsen BDS spins * Arbitron audience	1,086,816,456	1,353,805,426
log (exposures)	20.3723	0.9052
Mediaguide spins, Fall + Spring	45,477	12,785
log(spins)	10.6113	0.7279
Nielsen BDS spins (full year)	97,420	15,439
Explanatory Variables		
log(market population)	11.4011	1.7124
% Asian	1.6749	3.5772
% African American	6.4118	9.8222
% Hispanic	8.3886	17.2927
FM Power < 2	0.0453	0.2079
FM Power 2-5	0.1299	0.3362
FM Power 5-10	0.1154	0.3196
FM Power 10-20	0.0661	0.2485
FM Power 20-30	0.0604	0.2382
FM Power 30-60	0.1195	0.3244
FM Power 60-80	0.0116	0.1072
FM Power 80+	0.1678	0.3737
% Age 12-17	0.1010	0.0117
% Age 35-54	0.3383	0.0279
% Age 55 +	0.2741	0.0405
East North Central	0.1322	0.3387
East South Central	0.0933	0.2909
Middle Atlantic	0.0718	0.2582
Mountain	0.0933	0.2909
Pacific	0.1037	0.3049
South Atlantic	0.1453	0.3524
West North Central	0.1124	0.3158
West South Central	0.1254	0.3311
log(Class A Stations)	0.7290	0.9492
log(Class B Stations)	0.4936	0.9574
log(Class C Stations)	0.8430	1.1950
log(Class D Stations)	0.6791	1.0895
Black*Urban Format	1.0079	5.2703
Hispanic*Spanish Format	3.4277	14.6488
Owner #1 Rank	0.0610	0.2394
Owner #2 Rank	0.0131	0.1139
Owner #3 Rank	0.0096	0.0974
Owner #4 Rank	0.0082	0.0902
Owner #5 Rank	0.0692	0.2539
Owner #6 Rank 6-10	0.0441	0.2052
Owner #7 Rank 10-20	0.0287	0.1671

Table 4.2  
Station Data Set  
(continued)

Variable	Mean	Standard Deviation
Owner # 8, All other group owners	0.4216	0.4938
Digital signal	0.1059	0.3077
log(DMA households)	7.1308	1.0807
Class A Station	0.2638	0.4407
Class B Station	0.1655	0.3716
Class B1 Station	0.0227	0.1488
Class C Station	0.1349	0.3416
Class C0 Station	0.0197	0.1389
Class C1 Station	0.1089	0.3116
Class C2 Station	0.0839	0.2772
Class C3 Station	0.0789	0.2696
Classic Rock Format	0.0786	0.2692
Country Format	0.2707	0.4443
Jazz/New Age Format	0.0086	0.0925
Oldies Format	0.1052	0.3068
Rock Format	0.0970	0.2959
Spanish Format	0.1172	0.3217
Top 40 Format	0.0619	0.2411
Urban Format	0.0527	0.2235
Year = 2005	0.3329	0.4712
Year = 2006	0.3265	0.4689

For FM stations a series of dummy variables signifying the signal strength were constructed. Signal strength categories, expressed in kilowatts, range from under two to over 80. These class and power designations influence the quality and reach of the radio signal.

Ownership variables were constructed for the largest radio groups, including Clear Channel Communications, Inc., Infinity Broadcasting Corp. (now CBS Radio Inc.), Entercom Communications, Corp., Citadel Broadcasting Corp. and Cox Radio, Inc. Dichotomous variables were set equal to one for ranking group owners 6-10, 10-19 and all other stations owned by smaller groups.

Competition from other stations was indicated by the market's total number of Class A, B, C and D stations. These variables were expressed in logarithmic form. Also, dummies were created for digital stations and for the years 2006 and 2005.

Demographic characteristics included the 12+ population of the radio market area or primary coverage area, the market's population percentage for Asians, African Americans and Hispanics, individuals aged 12-17, 18-34, 35-54 and 55 and older and the population of the home DMA in households. Nine distinct regions of the country were identified. Urban and Spanish formats were interacted with the population percentages for African Americans and Hispanics, respectively.

#### *The Unavailable Data Challenge*

As indicated, ratings and music play time information were not available for a large number of stations. If such information is systematically unavailable (that is, if there are characteristics that are correlated with data availability and at the same time with music sales), then this deficiency could bias any effort to link sales with music exposures.

To explore whether this is the case, logistic regressions were used to link the probability of inclusion in the Arbitron, Nielsen BDS spins or Mediaguide spins samples to station and market characteristics. The results of this analysis are presented in Table 4.3. Clearly, results indicate that data availability is quite predictable. In particular, stations in large radio markets and those delivering a strong signal are more likely to meet Arbitron's minimum ratings standards and be covered by music monitoring services. Such stations have larger audiences and higher advertising revenues than stations in smaller radio markets. It is worth noting that the sign of the DMA household coefficient is negative for the Arbitron sample. This is because stations with a coverage population that is smaller than the home DMA are less attractive to regional advertisers trying to penetrate the larger market. In addition, stations face more competition from other media, especially television stations, in large DMAs. Finally, there are significant differences between format types. Stations with ethnic or religious formats are less commercially oriented, and are therefore less likely to have ratings or music play time information.

To make these relationships concrete, several simulations based on the model are provided in Table 4.4. The predictions represent the probability that a station with assumed characteristics will appear in the Arbitron, Nielsen BDS and Mediaguide samples, respectively. The base case represents a typical station with an Adult

Contemporary music format located in an average-sized radio market with a class C0 license (strong signal, favorable spectrum location). Almost 90 percent of such stations will have Arbitron ratings that meet minimum reporting standards, although spins data will be unavailable for most stations (only four percent and 17 percent representation in the Nielsen BDS and Mediaguide samples, respectively). However, for the largest markets within the largest DMAs, there are virtually no unavailable data.

Table 4.3  
Probability of Radio Station Having Audience and Spins Data

Dependent Variable (0,1)	In Arbitron Sample:		In Mediaguide		In Nielsen BDS Sample	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-1.7654	0.9124	-20.8147	1.0534	-23.2746	1.3183
log(DMA households)	-0.4501	0.0371	0.1576	0.0430	0.1375	0.0558
log(radio market pop)	0.5507	0.0295	1.0130	0.0420	1.1829	0.0557
% Asian	-0.0173	0.0077	-0.0419	0.0094	-0.0064	0.0089
% African American	-0.0187	0.0034	0.0049	0.0038	0.0206	0.0044
% Hispanic	-0.0038	0.0029	0.0014	0.0029	0.0011	0.0035
Population Growth	-1.3594	0.7820	0.1864	0.8380	-1.9297	1.0156
Class A Station	1.6658	0.1202	2.7685	0.2523	2.6371	0.3421
Class B Station	0.9260	0.1056	1.6833	0.2428	2.0017	0.3268
Class B1 Station	3.1448	0.4353	2.9469	0.3250	2.7435	0.4331
Class C Station	0.9822	0.1175	2.4200	0.2518	2.6290	0.3367
Class C0 Station	3.9822	1.0153	2.5624	0.3214	2.8018	0.3918
Class C1 Station	2.6519	0.2722	2.3831	0.2640	2.3711	0.3491
Class C2 Station	3.0285	0.2821	2.5366	0.2710	2.5316	0.3591
Class C3 Station	2.0803	0.1981	2.7271	0.2888	2.6818	0.3852
Adult Contemporary	0.7320	0.3807	4.3458	0.2181	5.7463	0.3994
Classic Rock Format	0.9765	0.4148	3.9522	0.2365	5.0456	0.4176
Country Format	0.4113	0.3739	4.1807	0.2219	5.6864	0.4044
Jazz/New Age Format	0.8162	0.5991	4.7356	0.4073	6.2319	0.5472
Oldies Format	0.2431	0.3856	4.0847	0.2486	3.8209	0.4648
Religion Format	-1.0014	0.3713	2.7124	0.2373	4.3338	0.4123
Rock Format	0.6149	0.3910	3.2287	0.2280	5.8520	0.4050
Spanish Format	-0.5077	0.3755	3.8492	0.2292	5.0679	0.4068
Top 40 Format	1.2588	0.4318	4.4032	0.2337	6.5109	0.4113
Urban Format	0.8530	0.4091	4.5095	0.2412	6.6242	0.4139

Note that smaller radio markets, especially those located within large DMAs are potentially problematic. Spins data are rarely provided and only about 65 percent of these stations meet Arbitron's minimum reporting standards. Lower power stations, in

particular Class D stations, are much less likely to be included. Data are unavailable for less commercial stations, especially those with lower ratings because of Arbitron's minimal reporting standards. For example, data are seldom available for ethnic formats such as Korean music or religious stations.

Recall that the music sales data provided by Nielsen SoundScan are compiled at the DMA level for only the 99 largest markets. Thus, data being unavailable for all markets may not be as significant a problem, especially if the analysis is restricted to general interest, commercial music genres.

Table 4.4  
Simulations of Probability of Stations Having Ratings and Spins Data

Scenario	Arbitron	Nielsen BDS	Mediaguide
Base Case	88	4	17
Largest Market, Largest DMA (10M), Top 40	100	99	98
Large Market, Large DMA (3M)	100	89	93
Small Market (100K), Large DMA	65	1	5
Small Market, Small DMA (200K)	86	1	3
Average Market, Small DMA	100	39	60
Small Market, Small DMA, Class D Station	54	1	3
Small Market, Large DMA, Class D, Religious	17	0	1
Small Market, Large DMA, Class D, Ethnic	5	0	0

Base Case: Average Market (500K), Average DMA (1M), Class C0,  
Adult Contemporary Format

However, most stations have broadcast audiences that spill into contiguous DMAs. In addition, small radio market stations located under the umbrella of larger DMAs are especially underrepresented. Thus, a method for addressing the unavailable data challenge is necessary if one is to have confidence in final results.



### *Methods for Data Imputation*

Two approaches were utilized to account for unavailable data. The first applied an ordinary least squares regression methodology (OLS), linking ratings and exposure information with known station characteristics. As an alternative, multiple imputation Markov Chain Monte Carlo techniques (MI) were utilized.<sup>41</sup> Table 4.5 outlines the structure and source of the resulting data sets.

The first data set is a mix of actual values for ratings and available exposures (ratings times spins, *rs*) and imputations based on a regression approach.<sup>42</sup> The second imputation also mixes actual and imputed values, but this time a MI approach is utilized.<sup>43</sup> The sample only includes stations for which there are reported Arbitron ratings, that is, stations that meet Arbitron's minimum reporting requirements. The final imputation also utilizes MI techniques but this time a full sample of values is created for all stations in the BIA Financial Network data set.

Table 4.5

#### Imputation Approaches

Data Set, Observations	Approach
Imputation m <sub>1</sub>	Series of OLS regressions of ratings and Nielsen BDS exposures, predicted as a function of station and market

<sup>41</sup> The MI method is detailed in Rubin, D.B. (1987), *Multiple Imputation for Nonresponse in Surveys*, New York: John Wiley & Sons, Inc. In each case, five separate imputations were created and combined using PROC MI from the SAS Institute software.

<sup>42</sup> Average predictions of levels based on a log model will tend to understate the actual values on average (this is because the average of the  $\log(x)$  is not equal to the  $\log(\text{average } x)$ ). Thus, a standard transformation was set equal to  $\exp(\bar{\epsilon})$ , the average of the sample exponentiated residuals. This transformation increased the predictions by an average of about 20 percent across all models.

<sup>43</sup> One advantage to the MI approach was that the technique also filled in unavailable values for all the covariates. Thus the data set, used subsequently for generating a full set of predicted values, is slightly more complete. It is noteworthy, however, that the correlation between methods was .95 and in analysis reported below, there was virtually no difference in empirical findings.

	<p>characteristics. Unavailable values code utilized only for Arbitron stations for which station data were unavailable.</p> <p>Step 1: If <math>e</math> (Nielsen BDS exposures) is missing, <math>m_1 = f(x, r, s)</math> where <math>x</math> represents station and market characteristics, <math>r</math> is Arbitron ratings data and <math>s</math> are Mediaguide radio spins, where available.</p> <p>Step 2: If <math>s</math> is also missing, then <math>m_1 = f(x, r)</math>.</p> <p>Step 3: If <math>a</math> is also missing, then <math>m_1 = f(x)</math>.</p>
Imputation $m_2$	Multiple imputation techniques. Five imputations utilized and averaged for sample of Arbitron stations only.
Imputation $m_3$	Multiple imputation techniques. Five imputations utilized and averaged for complete BIA Financial Network sample.

Table 4.6 reports the regressions utilized for the first imputation data set  $m_1$ . These regressions were also used to generate predictions for the complete data set as the first stage in the two-stage analysis of radio plays and the impact on music sales described below. The first model regresses Arbitron audiences at the station level in logarithms as a function of market and station characteristics. Note that the model for stations does well at predicting audiences with an  $R^2$  of about .75. Since we will end up summing these predictions for multiple stations at the DMA-level, the accuracy will be even higher in the aggregate.

Table 4.6  
Regressions to Impute Music Exposure

Variable	Log (Arbitron audience)		Log (Nielsen BDS exposures)		Log (Nielsen BDS exposures)		Log (NielsenN BDS exposures)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-1.6215	0.1852	9.5521	0.1407	10.3925	0.1107	11.7749	0.3789
log(Arbitron audience)	-	-	0.9910	0.0062	0.9825	0.0056	-	-
log(Mediaguide spins)	-	-	0.1147	0.0075	-	-	-	-
log(market population)	0.4786	0.0081	-0.0200	0.0055	-0.0140	0.0045	0.3446	0.0139
% Asian	0.0033	0.0019	0.0033	0.0012	0.0005	0.0006	0.0024	0.0020
% African American	-0.0022	0.0011	0.0000	0.0005	-0.0008	0.0004	0.0020	0.0014
% Hispanic	0.0018	0.0008	0.0007	0.0003	0.0004	0.0003	0.0021	0.0009
FM Power < 2	0.4850	0.0404	0.0413	0.0274	0.0565	0.0222	0.0638	0.0762
FM Power 2-5	0.4605	0.0325	0.0320	0.0219	0.0550	0.0193	0.1523	0.0661
FM Power 5-10	0.6188	0.0312	0.0453	0.0212	0.0519	0.0185	0.2070	0.0634
FM Power 10-20	0.8114	0.0354	0.0342	0.0224	0.0492	0.0196	0.2341	0.0672
FM Power 20-30	0.8385	0.0366	0.0429	0.0225	0.0403	0.0199	0.2357	0.0680
FM Power 30-60	0.8624	0.0321	0.0285	0.0218	0.0387	0.0193	0.1814	0.0661
FM Power 60-80	0.9400	0.0645	0.0212	0.0262	0.0373	0.0237	0.1502	0.0813
FM Power 80+	0.9988	0.0381	0.0237	0.0237	0.0383	0.0212	0.1523	0.0728
% Age 12-17	1.4951	0.9103	1.1325	0.5172	0.8816	0.4510	-5.2413	1.5424
% Age 35-55	0.7458	0.2828	0.1009	0.0797	0.0693	0.0762	-0.0628	0.2613
% Age 55 +	1.0028	0.2134	-0.0762	0.1197	0.0511	0.1008	-1.2902	0.3446
East North Central	-0.2186	0.0352	-0.0291	0.0147	-0.0151	0.0131	-0.1452	0.0447
East South Central	-0.1969	0.0431	-0.0240	0.0191	0.0021	0.0170	-0.2858	0.0582
Middle Atlantic	-0.0534	0.0371	-0.0107	0.0158	-0.0054	0.0136	0.0266	0.0467
Mountain	-0.3703	0.0453	-0.0447	0.0193	-0.0097	0.0174	-0.3473	0.0591
Pacific	-0.2779	0.0414	-0.0619	0.0181	-0.0339	0.0153	-0.3983	0.0519
South Atlantic	-0.2441	0.0386	-0.0375	0.0170	-0.0052	0.0149	-0.2383	0.0510
West North Central	-0.3042	0.0411	-0.0469	0.0194	-0.0096	0.0174	-0.1455	0.0597
West South Central	-0.2356	0.0432	-0.0390	0.0192	-0.0112	0.0170	-0.1886	0.0581

Table 4.6  
Regressions to Impute Music Exposure  
(continued)

Variable	Log (Arbitron audience)		Log (Nielsen BDS exposures)		Log (Nielsen BDS exposures)		Log (Nielsen BDS exposures)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
log(Class A Stations)	0.0990	0.0097	-0.0004	0.0039	0.0033	0.0036	0.0574	0.0124
log(Class B Stations)	0.1328	0.0148	0.0037	0.0075	0.0178	0.0067	0.1384	0.0228
log(Class C Stations)	0.1094	0.0122	0.0031	0.0076	0.0056	0.0069	-0.0116	0.0235
log(Class D Stations)	0.1160	0.0104	-0.0199	0.0045	-0.0193	0.0041	0.0397	0.0141
Black*Urban Format	0.0061	0.0021	-0.0028	0.0007	-0.0025	0.0006	0.0098	0.0021
Hispanic*Spanish Format	0.0007	0.0012	0.0028	0.0005	0.0029	0.0005	0.0073	0.0016
Owner #1 Rank	0.3759	0.0404	0.0745	0.0174	0.0682	0.0171	-0.1618	0.0583
Owner #2 Rank	0.5293	0.0563	0.0534	0.0191	0.0435	0.0187	-0.1055	0.0640
Owner #3 Rank	0.2743	0.0619	0.0546	0.0206	0.0567	0.0199	-0.2279	0.0680
Owner #4 Rank	0.3106	0.0649	0.1144	0.0237	0.1134	0.0224	-0.1555	0.0766
Owner #5 Rank	0.3348	0.0388	0.0343	0.0179	0.0346	0.0174	-0.3005	0.0593
Owner #6 Rank	0.4592	0.0431	0.0479	0.0184	0.0445	0.0179	-0.1562	0.0613
Owner #7 Rank	0.3180	0.0449	0.0106	0.0179	0.0072	0.0174	-0.1726	0.0595
Owner #8 Rank	0.2092	0.0345	0.0560	0.0176	0.0500	0.0171	-0.2614	0.0585
Digital signal	0.1940	0.0233	0.0017	0.0072	-0.0052	0.0066	0.0788	0.0227
log(DMA households)	0.1144	0.0082	-0.0011	0.0056	0.0059	0.0048	0.3001	0.0153
Class A Station	0.6124	0.0492	0.9224	0.0599	1.2238	0.0554	2.0096	0.1895
Class B Station	0.3993	0.0481	0.8956	0.0597	1.1906	0.0553	2.0200	0.1891
Class B1 Station	0.6104	0.0599	0.9203	0.0621	1.2503	0.0575	1.9658	0.1966
Class C Station	0.3263	0.0538	0.9220	0.0613	1.2315	0.0568	2.4808	0.1934
Class C0 Station	0.3712	0.0655	0.9024	0.0617	1.2111	0.0573	2.3558	0.1953
Class C1 Station	0.2326	0.0563	0.9302	0.0612	1.2428	0.0567	2.2889	0.1934
Class C2 Station	0.3663	0.0535	0.9140	0.0607	1.2345	0.0562	2.2569	0.1917

Table 4.6  
Regressions to Impute Music Exposure  
(continued)

Variable	Log (Arbitron audience)		Log (Nielsen BDS exposures)		Log (Nielsen BDS exposures)		Log (Nielsen BDS exposures)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Class C3 Station	0.4949	0.0550	0.8831	0.0622	1.2158	0.0572	2.1595	0.1954
Classic Rock Format	0.0643	0.0262	-0.1886	0.0123	-0.1997	0.0108	-0.1903	0.0371
Country Format	0.2439	0.0217	0.0433	0.0084	0.0521	0.0083	0.3187	0.0280
Jazz/New Age Format	0.1479	0.0606	-0.2365	0.0174	-0.2384	0.0175	-0.0498	0.0598
Oldies Format	0.0777	0.0285	0.1206	0.0197	0.1066	0.0190	0.2232	0.0653
Rock Format	-0.0093	0.0248	-0.1256	0.0122	-0.0981	0.0086	-0.1771	0.0293
Spanish Format	0.1047	0.0460	-0.2861	0.0209	-0.2867	0.0193	-0.3285	0.0661
Top 40 Format	0.1869	0.0266	0.0237	0.0084	0.0312	0.0083	0.1444	0.0283
Urban Format	0.4694	0.0518	-0.0471	0.0162	-0.0574	0.0152	0.2161	0.0517
Year = 2005	-0.0300	0.0167	0.0421	0.0064	0.0460	0.0059	0.0229	0.0204
Year = 2006	-0.0485	0.0169	0.0542	0.0064	0.0521	0.0059	-0.0038	0.0202
	R <sup>2</sup>	0.7449	R <sup>2</sup>	0.9818	R <sup>2</sup>	0.9806	R <sup>2</sup>	0.7723

The next three regressions link the log of music exposures, as provided by Nielsen BDS, with the same set of exogenous covariates. The first set utilizes the playtime information provided by Mediaguide. Not surprisingly, this model does an excellent job of predicting Nielsen BDS-provided exposures. Indeed, both organizations purport to measure the same outcome, so it would be disappointing if they did deviate significantly.<sup>44</sup> Since about 25 percent of the stations not covered by Nielsen BDS have Mediaguide information, this was an excellent source of additional information.

The next model utilizes ratings information to impute exposures in cases where both Nielsen BDS and Mediaguide spin data were unavailable. This model performs nearly as well as the previous model, suggesting that much of the variation in music exposure can be accounted for by ratings differences and exogenous market and station characteristics. The results suggest that the amount of music played by a station can vary significantly by format, market demographics, and station characteristics. For example, the “left-out” format variable is Adult Contemporary, so all the coefficients related to format can be viewed as comparisons with the Adult Contemporary base case. Thus, one finds that stations with Oldies formats play about 10 percent more music (about one song per hour), while Spanish formats play nearly 30 percent less than Adult Contemporary stations.

The final model links exposures to exogenous market factors, a set of results that will be useful in providing music exposure predictions for the complete sample of stations with or without ratings and/or spins information. Naturally, this model does not perform as well, but with an  $R^2$  of .77, predictions are accurate, especially if aggregated over multiple radio stations located in large geographic areas such as DMAs.

#### *Estimating the Effects of Radio Performance on Music Sales*

The next stage of the analysis was to link sales of music recordings to the aforementioned measures of music exposures on radio stations. As indicated, Nielsen SoundScan provided information on album sales and digital downloads of tracks, aggregated by DMA. These data are summarized in Table 4.7. Over the three-year

---

<sup>44</sup> The Nielsen BDS and Mediaguide measures would not be exact because of occasional technical failures and the fact that there are sometimes unaccounted for differences in coverage, especially with the inevitable format and ownership changes that can occur. In addition, Mediaguide spins were for two quarters, Fall and Spring, while the Nielsen BDS information covered the whole year. Still, with an  $R^2$  of over .98, the accuracy is outstanding.

period, sales of albums (primarily in the form of compact discs) averaged about 5.5 million in the 99 largest DMAs. Since the largest DMAs represent about 85 percent of the country's population, this suggests that total annual sales were nearly \$650 million annually. Digital track downloads averaged about 3.1 million over this time period. However, as discussed earlier, album sales were declining over this period (by about 13 percent) while digital downloads grew by over 600 percent. Indeed, in 2006 digital track sales exceeded the volume of albums.

Nielsen SoundScan also provided information on broad subcategories of album sales. About 64 percent of the total are considered "Current" or recently released recordings as opposed to older recordings, called "Catalog" albums. Other music genres analyzed were Country, R&B and Rap categories, representing about 12, 22 and 11 percent respectively.<sup>45</sup>

Since the primary outcome variables of interest were only made available at the DMA-level, information on radio stations had to be allocated at the same level. In cases where values were imputed, station outcomes were assigned to the home DMA. If, as is probable, these stations are more likely to be smaller stations with confined audiences, this method is likely to be accurate.<sup>46</sup> These audience measures are described in Table 4.8.

Actual ratings are expressed on a per capita basis for audiences listening to all music stations during an average quarter hour between 6 a.m. and midnight. Information is also for selected formats, including Urban, Oldies and Classic Rock and Country music. Actual reported exposures are also presented on a per capita basis. The mean value is just over 5,000 for all categories of music.

---

<sup>45</sup> Information on "Latin" genre sales was also made available, but these were not analyzed because of problems identifying Spanish music radio stations from other Spanish stations with formats that were primarily news, talk, or sports.

<sup>46</sup> As discussed, our final results were not sensitive to an alternative assumption, namely, that a station's audience distribution reflects the distribution that is typical of other stations located in the same DMA.

Table 4.7  
Nielsen SoundScan Data on Music Recording Sales 2004-2006

Music Sales (1000s)	DMA Mean	Standard Deviation
Albums	5,477	6,531
Tracks	3,132	5,951
Current	3,450	4,004
Top 100	2,103	2,322
Catalog	2,028	2,540
Country	648	424
R&B	1,246	1,576
Rap	616	732
Latin	290	501

Exposure data are also presented for imputed variables ( $m_2, m_3$ ). Numbers for the first set of imputations provided ( $m_2$ ), are about 50 percent higher than totals for the actual numbers reported (that is, those not imputed). This is because actual spins data were not available for most stations and adding imputed values increases totals significantly. The second set of imputations ( $m_3$ ) represents all radio stations in the BIA Financial Network data set, not just those for which the most reliable Arbitron ratings are available (those meeting minimum reporting standards).

Table 4.8  
Measures of Music Exposure by DMA

Measures:	Mean	Standard Deviation
Ratings Total	0.0882	0.0167
Ratings Urban	0.0108	0.0104
Ratings Oldies and Classic Rock	0.0137	0.0069
Ratings Country	0.0215	0.0115
Exposures Total	5,086	2,101
Exposures Urban	852	828
Exposures Oldies and Classic Rock	374	449
Exposures Country	1,177	811
Imputed Exposures Total ( $m_2$ )	9,246	2,359
Imputed Exposures, Urban ( $m_2$ )	1,082	974
Imputed Exposures, Oldies and Classic Rock ( $m_2$ )	1,463	869
Imputed Exposures, Country ( $m_2$ )	2,286	1,351
Imputed Exposures Total ( $m_3$ )	14,348	3,923
Imputed Exposures, Urban ( $m_3$ )	1,488	1,513
Imputed Exposures, Oldies and Classic Rock ( $m_3$ )	2,322	1,291
Imputed Exposures, Country ( $m_3$ )	3,794	2,121



Data were also gathered summarizing the demographics and economy of the DMA coverage area. For the most part, these data were based on county-level information and allocated to DMAs. In most cases every county was allocated to one and only one DMA.<sup>47</sup> In the eight cases where this was not true, data were allocated using the proportion of DMA listening household counts for each county. The complete set of covariates is provided in Table 4.9.

In addition to the actual ratings and music exposures and three sets of imputations, five sets of predictions ( $\hat{r}$ ,  $\hat{e}$ ,  $\hat{m}_1$ ,  $\hat{m}_2$ ,  $\hat{m}_3$ ) were also generated at the station level and allocated to DMAs. These predicted values were generated using the models for the Arbitron audience (reported in the first two columns of Table 4.6) and for Nielsen BDS exposures (reported in the last two columns of the same table). Note that these models can be viewed as “reduced form” expressions, because they predict ratings and exposures as a function of variables that can be considered to be exogenous. It is important that the models also contain a set of variables that are unlikely to affect music purchases *directly*, though they will have an indirect effect by influencing the amount of radio listening. These variables are station characteristics such as class of license, signal power and format.

Summing these predictions by DMA provides an additional set of explanatory variables to utilize in explaining album sales and digital track downloads. Since they are predicted rather than actual, the DMA levels are not affected by unobserved factors that are capable of influencing both recording sales *and* radio music airplay

---

<sup>47</sup> The FIPS (County) to DMA correspondence algorithm was derived from “U.S. Television Households, September 2005,” Nielsen Media Research. The following information was allocated in this manner:

Retail employment, unemployment, average household earnings and total income were downloaded from the Bureau of Labor statistics (<http://stats.bls.gov>).

Population counts were downloaded from the US Census Bureau Web site, [www.census.gov](http://www.census.gov). Population by age was obtained at the FIPS level. Population by age group was originally at the ZIP code level. These counts were aggregated from ZIP code to FIPS using the ZIPList5 Geocode file from CD Light (available on [www.zipinfo.com](http://www.zipinfo.com)). Population by ethnicity was downloaded at the FIPS level.

Information on Internet usage was taken from the Current Population Survey, October 2003: School Enrollment and Computer Use Supplement. The CPS reports results at several geographic levels. However, estimates formed for geographic areas smaller than states are not considered to be reliable. To obtain estimates for DMA counts, state level data were first allocated to FIPS based on a county’s share of total state population 18 years and over. These FIPS level data were then aggregated to DMAs.

Data on average commuting times were provided by Arbitron.

Table 4.9  
DMA-Level Data

Variable	Means	Standard Error
East North Central	0.0909	0.2880
East South Central	0.1111	0.3148
Middle Atlantic	0.0707	0.2568
Mountain	0.0606	0.2390
Pacific	0.0808	0.2730
South Atlantic	0.1919	0.3945
West North Central	0.1010	0.3019
West South Central	0.1313	0.3383
Log(population 12+)	1,975,778	2,265,297
% Asian	0.0216	0.0251
% African American	0.1140	0.0984
% Hispanic	0.0832	0.1060
% Age 18-24	0.1130	0.0166
% Age 25-34	0.1593	0.0164
% Age 35-44	0.1841	0.0104
% Age 45-54	0.1567	0.0080
% Age 55-64	0.1026	0.0097
% Age 65+	0.1506	0.0298
log(population with access to Internet)	468,240	565,272
log(population with DSL connections)	74,021	105,872
log(population with cable connections)	101,347	155,729
log(population downloading entertainment media)	91,605	111,651
log(hourly earnings)	16.02	1.80
log(commute)	23.53	3.13
log(average commuting time)	41,665	6,360
log(unemployment rate)	5.11	1.16
log(retail wage)	448.92	53.26
% Retail employment	0.1191	0.0952
% Construction	0.0567	0.0653
% Food Services	0.0703	0.0621
% Manufacturing	0.1192	0.0771
% Health Care	0.1015	0.0708
log(radio stations)	49.13	18.86
% Class A stations	0.2750	0.1468
% Class B stations	0.2228	0.2131
% Class B1 stations	0.0206	0.0357
% Class C stations	0.1449	0.1410
% Class C0 stations	0.0284	0.0481
% Class C1 stations	0.0790	0.0881
% Class C2 stations	0.0641	0.0709
% Class C3 stations	0.0631	0.0651

simultaneously. By utilizing these predictions rather than actual levels, one can be more confident that any observed correlation reflects a causal relationship.

It is also worth mentioning that these models explain a significant portion of observed ratings and exposures to music with  $R^2$ s of .74 and .77 respectively. Indeed, at the DMA level the explanatory power is even greater, because regression inaccuracies tend to balance out when multiple predictions for individual stations are aggregated. For ratings, the correlation between actual ratings (in logarithms) and the ratings predicted by the model is .951 at the DMA level. For exposures, the correlation is even higher, at .987. This close correspondence suggests that the potential for biases due to the omission of key explanatory variables is at a minimum.

#### *The Impact of Radio Playtime*

In Table 4.10, regression results for six categories of DMA music sales are reported. The categories analyzed are total albums, digital tracks, and four subsets of album sales: Catalog, Urban (R&B plus Rap), Country and Current. The dependent variables were expressed as logarithms of total sales. In this set of regressions, predicted values for the full set of imputed measures of music exposures were utilized ( $\hat{m}_3$ ). These values were expressed as exposures per capita, measured in thousands. Thus, the sample mean of 14,438 took on the value of 14.438 in the regressions. For the first broad categories representing all genre sales, the exposures were measured for the full set of popular music radio formats, including Adult Contemporary, Country, Classic Rock, Oldies, Jazz/New Age, Rock, Spanish, Top 40, and Urban.<sup>48</sup> For the “Catalog” genre, exposures were compiled for Classic Rock and Oldies stations only. The Urban and Country music album sales were also linked with radio music exposures for those genres only.

---

<sup>48</sup> These formats were selected on the basis of comparisons between playlists of radio stations and sales of particular albums. For other formats, such as Classical Music, Big Band or Nostalgic, Inspirational or Christian Music, the tracks typically played could not be found on comprehensive lists of record sales. Thus, the analysis was restricted to the aforementioned music genres and the radio formats that emphasize them.

Table 4.10  
Impact of Music Exposures ( $m_3$  Predicted) on Recording Sales

Variable	Log (Albums)		Log (Tracks)		Log (Current)		Log (Catalog)		Log (Urban)		Log (Country)	
	Coeff.	Stand. Error	Coeff.	Stand. Error	Coeff.	Stand. Error	Coeff.	Stand. Error	Coeff.	Stand. Error	Coeff.	Stand. Error
Intercept	-13.1198	1.8308	-36.4887	2.1790	-5.7335	1.7807	-8.1332	2.1569	-9.3350	2.7137	-1.6031	2.3339
Exposures per cap predicted*	0.0097	0.0022	0.0112	0.0026	0.0090	0.0021	0.0236	0.0074	0.0217	0.0130	0.0399	0.0058
year = 2006	-0.1624	0.0180	1.9312	0.0214	-0.1988	0.0175	-0.1051	0.0212	-0.4336	0.0259	-0.0806	0.0222
year = 2005	-0.1028	0.0153	1.4047	0.0182	-0.1230	0.0148	-0.0700	0.0181	-0.1719	0.0224	-0.0538	0.0193
East North Central	0.0139	0.0353	-0.0211	0.0420	0.0330	0.0343	-0.0029	0.0416	0.0243	0.0523	0.1524	0.0465
East South Central	0.0639	0.0379	-0.0437	0.0451	0.0249	0.0369	0.1215	0.0455	0.0170	0.0564	-0.0821	0.0483
Middle Atlantic	0.0695	0.0483	0.1584	0.0574	0.0455	0.0469	0.1187	0.0573	0.2010	0.0717	-0.0585	0.0628
Mountain	0.1740	0.0454	0.1626	0.0540	0.1084	0.0441	0.2732	0.0539	0.1700	0.0678	-0.1482	0.0581
Pacific	0.1433	0.0608	0.2168	0.0724	0.0922	0.0592	0.2005	0.0721	0.1682	0.0911	0.0160	0.0778
South Atlantic	0.0351	0.0403	0.0777	0.0480	0.0540	0.0392	0.0101	0.0478	0.0808	0.0603	0.1707	0.0528
West North Central	-0.0111	0.0289	0.0827	0.0344	-0.0138	0.0281	0.0049	0.0343	-0.0128	0.0432	-0.0115	0.0381
West South Central	-0.0216	0.0371	0.0151	0.0441	-0.0200	0.0360	-0.0307	0.0439	-0.0735	0.0552	0.2060	0.0486
log(population 12+)	0.4292	0.1839	1.1174	0.2189	0.4294	0.1789	0.3961	0.2185	0.5512	0.2747	0.9500	0.2364
% Asian	-0.5917	0.5335	-1.0499	0.6350	-0.6201	0.5189	-0.2016	0.6298	0.2075	0.7924	-3.1888	0.6817
% African American	0.2840	0.1354	-0.2362	0.1611	0.2839	0.1317	0.3715	0.1596	2.0192	0.2624	-1.4325	0.1749
% Hispanic	0.0955	0.1115	0.2448	0.1326	0.1241	0.1084	0.1463	0.1288	0.6332	0.1783	-1.1043	0.1387
% Age 18-24	3.9405	1.5054	12.0067	1.7917	3.0176	1.4641	5.5384	1.7926	5.6269	2.2515	-1.4569	1.9145
% Age 25-34	-1.0633	1.4116	2.0202	1.6801	-0.3178	1.3730	-2.6689	1.6745	-5.7863	2.1062	-0.5291	1.8079
% Age 35-44	3.1282	2.5346	9.9828	3.0166	1.9821	2.4651	4.7352	3.0030	9.5371	3.7788	-9.9548	3.2438
% Age 45-54	2.5563	1.8735	7.5317	2.2298	1.4618	1.8222	4.1464	2.2247	-4.3570	2.9134	4.9719	2.4054

Table 4.10 (continued)  
Impact of Music Exposures ( $m_3$  Predicted) on Recording

Variable	Log (Albums)		Log (Tracks)		Log (Current)		Log (Catalog)		Log (Urban)		Log (Country)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
% Age 55-64	5.7517	2.1413	4.2537	2.5485	5.3721	2.0826	6.1623	2.5426	12.1269	3.1877	4.9090	2.7147
% Age 65+	-0.2270	1.0559	5.1618	1.2567	-0.6672	1.0270	0.2393	1.2511	-1.3282	1.5980	-6.1665	1.3608
log(Web)	0.6944	0.2148	-0.0053	0.2557	0.6624	0.2090	0.8474	0.2563	0.6041	0.3215	-0.0844	0.2755
log(DSL)	-0.1910	0.0366	-0.1269	0.0436	-0.1567	0.0356	-0.2486	0.0435	-0.2130	0.0546	0.0209	0.0470
log(Cable)	-0.1026	0.0360	0.0916	0.0429	-0.0887	0.0350	-0.1332	0.0426	-0.0337	0.0536	-0.1304	0.0461
log(Web Media)	0.1583	0.0912	-0.0254	0.1086	0.1363	0.0887	0.1275	0.1084	0.0344	0.1388	0.1620	0.1165
log(hourly earnings)	-0.1677	0.1118	-0.2758	0.1331	-0.1385	0.1088	-0.2200	0.1331	-0.0247	0.1665	-0.2279	0.1446
log(commute)	0.1015	0.1192	0.6300	0.1419	0.0702	0.1160	0.1473	0.1427	0.0428	0.1747	-0.2870	0.1501
log(income)	0.4470	0.1315	1.4764	0.1566	0.4755	0.1279	0.3934	0.1560	0.5574	0.1958	0.5670	0.1696
log(unemployment rate)	-0.1042	0.0451	-0.2289	0.0537	-0.0823	0.0439	-0.1312	0.0537	-0.0555	0.0675	-0.0671	0.0578
log(retail wage)	0.2664	0.1800	0.7817	0.2142	0.1639	0.1751	0.3969	0.2134	0.3827	0.2688	-0.0881	0.2309
% Retail employment	-3.7468	0.9508	-0.9955	1.1316	-3.8427	0.9247	-3.2624	1.1258	-4.9022	1.4164	-2.9887	1.2276
% Construction	1.5016	0.3664	-0.0600	0.4360	1.5428	0.3563	1.4332	0.4345	2.1003	0.5484	0.6450	0.4726
% Food Services	6.7369	1.3738	1.8037	1.6351	6.4083	1.3362	6.8820	1.6312	7.5909	2.0511	5.2367	1.7812
% Manufacturing	-0.7166	0.2047	-0.4557	0.2436	-0.6460	0.1990	-0.9179	0.2414	-0.7664	0.3030	-1.3251	0.2566
% Health Care	-1.2584	0.5651	0.2972	0.6726	-0.9701	0.5496	-1.7944	0.6699	-0.7552	0.8431	0.0493	0.7234
	R <sup>2</sup>	0.9841	R <sup>2</sup>	0.9919	R <sup>2</sup>	0.9848	R <sup>2</sup>	0.9783	R <sup>2</sup>	0.9712	R <sup>2</sup>	0.9509

\*Predicted per capita exposures (in 1000s), imputed for full sample of stations ( $m_3$ )

The models indicate that music exposures have a positive and statistically significant impact on retail music sales. Coefficient estimates across all categories are significant at the 99 percent level. Table 4.11 presents simulations, indicating the percent impact due to a one-standard deviation increase in exposures as well as increases in a subset of independent variables. For albums, a one-standard deviation increase in exposures (equivalent to about 10 additional tracks of music per day) results in a two percent increase in album sales. For digital tracks, the equivalent number is 2.4 percent. Country music sales appear to be the most responsive, at 3.2 percent, while the increase in R&B and Rap album sales is lowest at one percent.

Significant time trends are apparent, with total album sales falling by over 10 percent from 2004 to 2005 and by 16 percent from 2004 to 2006, holding other factors constant. The declines in R&B and Rap were particularly pronounced, while the declines in Catalog and Country music sales were mild. On the other hand, the regressions highlight the dramatic increases in digital track downloads that have occurred over this three-year period.

Market demographic and economic factors clearly play a large role and coefficient estimates are, for the most part, unsurprising. For example, income is positively related to music sales of all types, with tracks showing the largest expansion at 22 percent. For similar reasons, sales are negatively related to unemployment levels. With the exception of Country music, sales are highest when retail wages are highest. Wage rate was included to better measure wage opportunities for youth and to reflect market by market differences in the nature of retail trade.

Table 4.11  
Impact of Independent Variables:  
Percent Increase in Sales Due to One Standard Deviation Increase  
in Exposure to Music on Over-The-Air Radio

	Albums	Tracks	Current	Catalog	Urban	Country
Exposures per cap	2.0%	2.4%	1.9%	2.0%	1.0%	3.2%
% Asian	-1.5%	-2.6%	-1.6%	-0.5%	0.5%	-8.0%
% African American	2.8%	-2.3%	2.8%	3.7%	19.9%	-14.1%
% Hispanic	1.0%	2.6%	1.3%	1.6%	6.7%	-11.7%
% Age 18-24	6.5%	19.9%	5.0%	9.2%	9.3%	-2.4%
% Age 25-34	-1.7%	3.3%	-0.5%	-4.4%	-9.5%	-0.9%
% Age 35-44	3.3%	10.4%	2.1%	4.9%	9.9%	-10.3%
% Age 45-54	2.0%	6.0%	1.2%	3.3%	-3.5%	4.0%
% Age 55-64	5.6%	4.1%	5.2%	6.0%	11.8%	4.8%
% Age 65+	-0.7%	15.4%	-2.0%	0.7%	-4.0%	-18.4%
log(income)	6.7%	22.0%	7.1%	5.9%	8.3%	8.4%
log(unemployment rate)	-2.2%	-4.9%	-1.8%	-2.8%	-1.2%	-1.4%
log(retail wage)	3.1%	9.0%	1.9%	4.6%	4.4%	-1.0%

The variables describing Internet use are highly significant, but difficult to interpret given their high degree of co-linearity. Further, these data were only available from the 2003 CPS and the cross-sections patterns may not accurately reflect changes that have occurred since that year. Note that these variables were the only ones in the data set that were not available on a county basis, making allocation to DMAs challenging.<sup>49</sup> In general, access to the Internet appears to be positively related to sales. On the other hand, cable connections to the Internet is negatively related to album sales, and positively related to track download purchases.

#### *Sensitivity of Results to Alternative Audience Measures*

<sup>49</sup> Results were not sensitive to the exclusion of these numbers. In addition, their levels were interacted with the dummy variables signifying different years to allow for the possibility that their relevance could have been evolving over this time period. These interactions were not significant. Finally, many of the sensitivity tests reported below do not indicate that systematic regression error is a problem in these estimates.

This section reports a number of additional estimates designed to test the sensitivity of the previous empirical results to the particular assumptions made. A subset of the regressions was re-run, using many of the alternative music exposure measures described earlier. The following measures were examined with results reported in appendix Tables B.1 through B.6:

1. Actual Arbitron ratings, no imputations ( $r$ )
2. Predicted Arbitron ratings, no imputations ( $\hat{r}$ )
3. Actual exposures, no imputations ( $e$ )
4. Predicted exposures, no imputations ( $\hat{e}$ )
5. Predicted exposures, econometric imputations for Arbitron sample ( $\hat{m}_1$ )
6. Predicted exposures, MI imputations for Arbitron sample ( $\hat{m}_2$ )

All six measures yielded results that were consistent with those reported for the full sample of predicted imputations. All coefficients were positive and significant.

Interestingly, using the actual Arbitron ratings, without considering the amount of music played by station, filling in values that are unavailable, or accounting for factors that could create spurious correlations *increased* the estimated effect. The coefficient estimate for albums suggests that a one-standard deviation increase in observed ratings (an increase of .0167) yields about a four percent increase in album sales. All the other measures yielded estimates that are remarkably consistent with one another.

Next, alternative assumptions were made about the functional form assumed to characterize the relationship between music sales and radio exposures. These regressions are reported in appendix Tables B.7 and B.8. Next, estimates are provided for additional genre categories, including Latin and “Top 100” albums. These are reported in appendix Table B.9.

#### *Alternative Functional Forms*

In the reported regressions, it was assumed that the appropriate model expressed music exposures on a per capita, linear basis. This characterization implicitly assumes a *linear* relationship, i.e., that increases in exposures result in constant percentage increases (or decreases) in music recording sales. If violated in reality, this assumption will affect the interpretation of results significantly under two conditions:



1. The range of exposures observed currently is limited, but policy changes may significantly alter the levels of radio reliance on music (for example, in response to performance fees).

2. The important policy question revolves around the question of what the *total* contribution of radio play is, in contrast to increases on the margin.

Since these conditions may be relevant to the policy debate, alternative assumptions about the relationship were analyzed. The two alternatives considered bound the per capita, linear model presented earlier. The first expresses exposures in logarithms. The upshot of this model is that it assumes a constant percentage relationship between sales and exposures. The second approach assumes a logistic functional form that is consistent with prevailing theories of advertising effectiveness.<sup>50</sup> The logistic function is shaped like an “S-Curve.” This shape is consistent with an advertising response function in which initial exposures are not very effective. But, once a certain threshold is exceeded, the advertising is effective.

Estimates from the logarithmic model are presented in appendix Table B.7. The logistic, or S-Curve model is presented in Table B.8.<sup>51</sup> The most important point to be made is that the impact of music performance on radio stations is positive and significant, regardless of which assumption is made. For the logarithmic model (using the audience measure  $\hat{m}_3$ , predicted values for the full sample of stations), the estimates indicate that the elasticity of album sales with respect to exposures is about .14. In other words, a 20 percent increase in exposures leads to a 2.8 percent increase in album sales. These results are similar to those obtained using the per capita or linear model. For Tracks and Catalog, Current, Country and Urban genres, the impacts are also positive, consistent and very similar to those obtained with the per capita model.

The logistic or S-Curve estimates also yield similar results. These estimates suggest that sales of albums and digital tracks increase up to 15.5 percent and 15.0 percent, respectively. These coefficient estimates are significant at the 99 percent level.

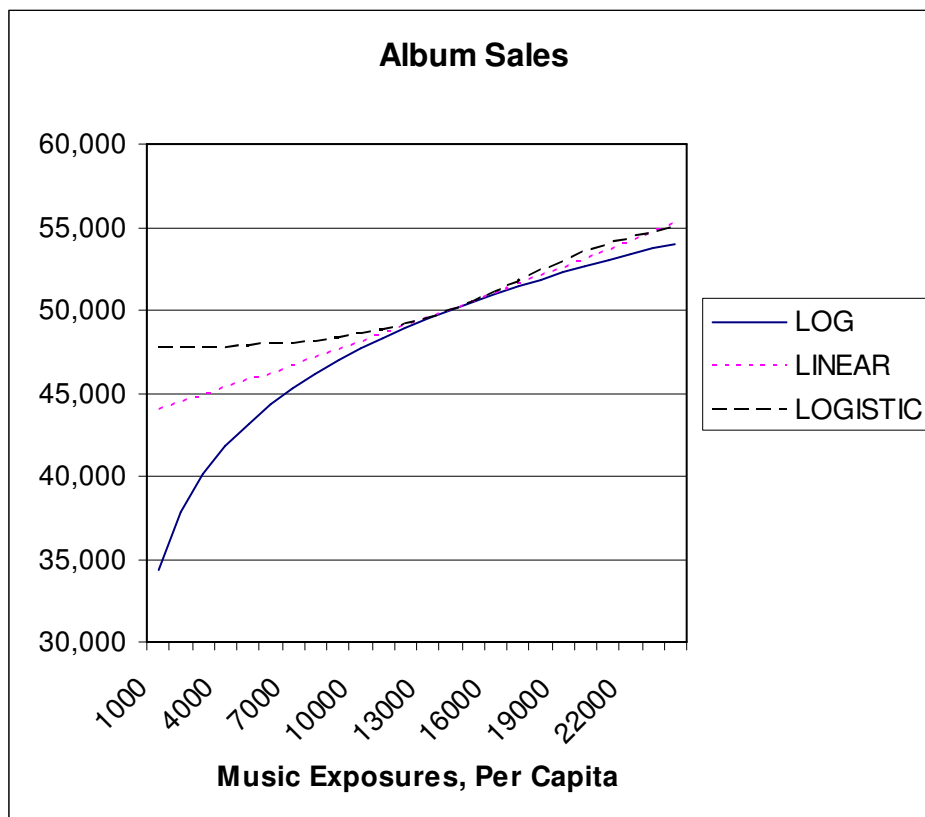
---

<sup>50</sup> For example, see Dertouzos and Garber (2006).

<sup>51</sup> Formally, the logistic function specified the promotional effect as:  $\kappa/(1 + \exp(\beta - \mu \hat{m}_3))$ , where  $\kappa$  represents the percentage increase at which saturation occurs (the maximum increase possible),  $\beta$  is an arbitrary scale parameter (assumed to be five in these estimations). The goodness of fit is largely unchanged with different assumptions concerning  $\beta$ . Finally,  $\mu$  represents the speed with which the saturation point is achieved.

Although these empirical effects are similar in magnitude, they each have different implications for the value of radio promotion over the whole range of music exposures. In Figure 4.1, music sales are projected based on the empirical estimates of the three alternative models. Note that the linear model is bound by the logistic and logarithmic model. That is, the logistic model estimates a lower value at low levels of exposure, as well as diminishing returns at high levels. The logarithmic estimates indicate diminishing returns over the whole range of exposures. The linear, per capita model assumes a constant effect over the whole range. The upshot of the difference is that if one were to use these estimates to calibrate the total value of radio play for recording music sales, the per capita estimates would be in the middle.

Figure 4.1  
Implications of Alternative Functional Forms



In choosing among the three, the best criterion would be how well the models fit the data, or goodness of fit. In terms of explaining variance, the per capita, linear model performs slightly better than either of the other two in terms of  $R^2$ . A more important

point, however, is that estimates of promotional effectiveness of radio airplay are not very dependent on functional form. As in the case of choice of exposure measures, the impact is significant and positive over all options.

#### *Examination of Separate Music Genres*

In appendix Table B.9, separate models are estimated for different genres. In comparison to the regressions presented earlier, music exposures are expressed as total exposures to all album genres. This is in contrast to the models presented in Table 4.10, in which exposures were measured for narrow music formats that corresponded closely with the individual album genres. These results are interesting because they indicate that the estimated benefit of radio music performance applies across multiple genres. The only category in which positive and significant impacts are not obtained is for Latin album sales. This is the one category of BIA Financial Network-provided format that does not distinguish between music and other sorts of programming. Thus, there is an element of error not relevant for other genres.

#### *Sensitivity to Econometric Methods*

In this section, alternative econometric approaches to the problem are explored. First, estimates were derived using standard two-stage least squares methodologies. These estimates, reported in appendix Table B.10, utilize exposure data (imputed for the subset of Arbitron stations where spins data ( $m_2$ ) are unavailable). Rather than using predictions for individual stations, predicted values for exposures are derived in a first-stage regression linking DMA-level audience exposures with a full set of exogenous variables, including summary measures measuring the number of local radio stations and their characteristics.<sup>52</sup> In these models, exposures were expressed in logarithms because the first-stage predictive model was more accurate in this form. The estimated elasticities provide sales responsiveness measures that are quite consistent with the relationships estimated using sums of the predicted measures for individual stations.

Next, several tests for heteroscedasticity were performed. As discussed, there are some data inaccuracies that are likely to vary systematically. For example, variables such as the CPS Internet data are likely to be more accurate for largest DMAs or DMAs that

---

<sup>52</sup> Standard endogeneity tests that regress music sales on both the actual level of exposures as well as the prediction of exposures indicate that the endogeneity assumption (and choice of station descriptions as instruments) is appropriate.

correspond to MSA geographic units. Other variables, such as Arbitron and exposure data, are more complete for large DMAs. Finally, some of the variables, such as population numbers from the Census, were taken for years preceding 2004 and were not adjusted for population growth. While these numbers do not change significantly from year to year and the estimation technique relies primarily on cross section rather than time series variation, there remains an element of error introduced.

In appendix Table B.12, the results of this analysis are presented.<sup>53</sup> In these exercises, the size of the regression error (the absolute value of the regression residual) was regressed on the MSA coverage percentage, the size of the DMA, the percentage of stations with Arbitron data, and the dummy variables indicating the year. For the eight regressions (analysis for both albums and tracks for four predictors), only one indicated a significant relationship. In the albums model, the regression residual averaged roughly 20 percent higher in 2004 in comparison with the latter two years. To account for this, weighted least squares were performed. Not surprisingly, given the magnitude of the absolute difference in residuals for 2004, the WLS results were virtually identical.

In addition to these tests for heteroscedasticity, alternative approaches to allocating stations to DMAs were examined. In the allocations reported earlier, station audience data were allocated to DMAs based on Arbitron samples of U.S. households. As discussed, a large number of stations do not have audience evidence that meets Arbitron reporting requirements. For these stations, imputed data sets were created, under the assumption that audience levels could be predicted as a function of observable station and market characteristics. However, these models do not produce the distribution of these audiences across DMA boundaries.

For stations not meeting Arbitron's minimum reporting standards, data were imputed and predicted values were allocated based on the identity and location of the primary radio market. For this sample of stations, many more of which are small stations

---

<sup>53</sup> Recall that in analysis provided by Leibowitz, it was assumed that regression errors were a function of DMA size, under the assumption that matching MSA to DMA was less accurate for small DMAs. While the latter is true, Leibowitz conducted no specific tests to see whether, in fact, such heteroscedasticity is prevalent or relevant. This is an important point, because the scheme he used to place considerable weight on the largest DMAs was a key factor that drove his results. Since most of our variables were initially gathered on a county rather than a MSA level, one would not expect that a weighting scheme (using a weighted least squares approach) would improve efficiency. As discussed above, this proved to be the case.

with less powerful signals and more confined market areas, the audiences are probably confined to the home DMA. However, to test the sensitivity of the final results to this assumption, an alternative allocation was made based on assuming that each station for which data were not available had a distribution across DMAs that reflected the average distributions for the other stations in the same home market for which ratings information was available. It is likely that these two alternative approaches bound the range of possibilities and, therefore, utilizing both approaches provides a rigorous sensitivity test.

The results of this test are reported in appendix Table B.13. The estimated coefficients are very similar, regardless of the method. In fact, the chosen approach leads to estimated effects that are even smaller, and can therefore be viewed as a conservative estimate of the true relationship between music exposures and recording sales.

#### *Estimates from a Fixed Effects Model*

The last set of estimates was obtained from a model that closely approximates the methodology utilized by Liebowitz (2006). For reasons discussed earlier, the fixed effect approach removes virtually all of the cross section variation from the data. Unless covariates (such as market demographics, radio station descriptions, and listening behavior) vary significantly over time, this approach is likely to be quite inefficient, thereby leading to imprecise and possibly misleading estimates. For completeness, however, estimates were obtained using a version of the model that most closely approximates the approach used by Liebowitz. In our model, the dependent variable was expressed as album sales per capita. A limited set of covariates was used, reflecting the fact that most of the others do not vary sufficiently over time (though they do vary significantly from area to area). We included a separate dummy variable for each of the sample DMAs. Finally, although we found no evidence supporting the existence of systematic error patterns by DMA, we performed a weighted least squares using weights that are similar to those used by Liebowitz.

The resulting estimates are quite different for the weighted and unweighted versions. While Liebowitz found negative coefficients in his study, our coefficients remain positive and significant for both versions. Indeed, the computed effects are far in excess of those estimated using the preferred methodology. Results here show that the Liebowitz model and data are incomplete. Further, his model does not adequately account

for a whole host whole host of variables that can affect the relationship between radio airplay and music sales, while our models do account for these effects.

*Summary of Empirical Results*

Table 4.12 summarizes the key empirical results for the primary measures of interest, namely album sales and digital track downloads. The results are expressed as total percentage increases, computed over the whole range of exposures, that can be attributed to the performance of recorded music on radio stations.

For albums, the estimates range from a low of 14 percent to a high of 23 percent. For tracks, the estimated impacts range from a low of 15 percent to a high of 20 percent, depending on the method used.

Table 4.12  
Comparison of Results:  
Expansion of Recording Sales Due to Music Performance  
on Over-the-Air Radio

Model	Method	Albums	Tracks
1.	Raw Arbitron Ratings, Ordinary Least Squares	23%	20%
2.	Music Exposures (logarithmic model), Two-Stage Least Squares	22%	19%
3.	Music Exposures (per capita), predictions for full station sample	14%	16%
4.	Music Exposures (logarithmic model), predictions for full sample	14%	15%
5.	Music Exposures (logistic model), predictions for full sample	16%	15%

## ***5. Summary and Policy Implications***

Historically, the radio and recording industries have enjoyed a mutually beneficial relationship. Over 70 percent of the nation's radio stations compete in the media marketplace by providing free, over-the-air music entertainment to listeners. Although composers and publishers receive royalties for the performance of such music, performers and record labels also profit from the exposure provided by airplay through the reproduction, distribution and sale of music recordings. Under this arrangement, both parties expect to profit. The recording industry receives indirect revenues when audiences like and purchase the music they hear. Local radio stations receive revenues from advertisers that pay for access to listeners who are potential customers for the goods and services they are offering. These same listeners generate revenues for the recording industry as customers induced to purchase recordings they have heard on the radio. In essence, we have found that radio exposure is free advertising.

In today's rapidly evolving and uncertain environment, old questions are being asked anew about this symbiotic equilibrium. Of interest here is the question, does the absence of a performance fee for performers and record labels still make sense in this increasingly competitive environment?

Unfortunately, the ongoing debate suffers from the scarcity of rigorous research capable of providing answers to this fundamental question. The goal of this research project was to begin to fill this void. While many issues remain unresolved, the following conclusions are clearly supported by the research:

Previous evidence, in the form of survey research and the persistence of standard industry practices to promote airplay, strongly suggest that new performance fees for performers and record labels is not justified.

The sale of recorded music, at least in terms of revenue production, is lagging behind the growth apparent in other media sectors. This trend is unlikely to change. However, increases in digital sales and Internet activity, the adoption of MP3 players and the comfort of younger generations with new technologies, suggest that new opportunities abound. There is no evidence that radio has played any part in the music

industry's decline. Further, there is no evidence that radio's role in promoting music has diminished.

Economic theory suggests a wide range of circumstances under which record labels would be willing to provide music voluntarily to radio stations at no cost. In fact, one could imagine feasible circumstances in which record labels would pay to have their music promoted. This would be particularly true for recording artists who stand to gain concert and licensing revenue from the promotion of their music.

That record labels would pay (rather than charge) for music exposure would especially be true in markets where independent entities make independent business decisions on their own behalf. Healthy competition between business rivals would likely result in free-market payments by record labels to promote their individual releases and garner radio airplay, even if industry sales suffer as a result. This implies that a positive relationship between industry sales and aggregate radio play of music is a sufficient condition for validating the existence of a promotional impact, significantly tipping the scale against efficacy of new performance fees for performers and record labels.

Recent research on this issue has been flawed, either because of poor methods and data or an inappropriate market context for interpreting results. As we noted, a positive promotional impact for a single album may not be as relevant as the group of music products likely to represent the bargaining unit that is relevant to a record label.

This study resolved several methodological challenges in addressing the key empirical question of whether radio play improves music industry sales. By constructing an appropriate measure of radio exposure, addressing significant data deficiencies and utilizing an approach designed to overcome the potential for spurious correlation, reliable estimates of the promotional effects from radio airplay were obtained. These results were especially noteworthy because of their magnitude, their high statistical significance and because they are remarkably insensitive to a variety of econometric methods, assumptions and measurement techniques.

Most importantly, results demonstrate that a significant portion of industry sales of albums and digital tracks – at minimum 14 percent and as high as 23 percent – is attributable to radio airplay, suggesting that radio is already providing a significant sales benefit that ranges between \$1.5 and \$2.4 billion in incremental revenue annually. If a



performance fee were enacted, stations could reduce music airplay, change formats and even cease to operate, resulting in the loss of much of this promotional benefit.

## ***References***

- Anderson, Chris, "The Long Tail," *Wired*, October 2004.
- Bard, Robert L. and Lewis S. Kurlantzick, "A Public Performance Right in Recordings: How to Alter the Copyright System Without Improving It," *George Washington Law Review*, November 1974, Vol. 43, No. 1.
- Dertouzos, James N. and Steven Garber, *Is Military Advertising Effective?*, RAND Corporation, Santa Monica, R-1591-OSD, 2003.
- Dertouzos, James N. and Steven Garber, "Effectiveness of Advertising in Different Media," *Journal of Advertising*, Summer 2006.
- Dertouzos, James N. and Steven S. Wildman, *A Study of Economic Issues in the Recording Industry*, August 1979.
- Krasilovsky, M. William and Sidney Shemel, *This Business of Music*, New York: Billboard Books, 10<sup>th</sup> Edition, 2007.
- Liebowitz, Stan J., *Don't Play It Again Sam: Radio Play, Record Sales, and Property Rights*, Draft, January 5, 2007.
- Leibowitz, Stan J., "Pitfalls in Measuring the Impact of File-sharing on the Sound Recording Market," *CESifo Economic Studies*, Vol. 51, 2-3/2005, 435-473.
- Montgomery, Alan L. and Wendy W. Moe, "Should Music Labels Pay for Radio Airplay? Investigating the Relationship Between Album Sales and Radio Airplay," August 2002.
- Mortimer, Julie Holland and Alan Sorensen. "Supply Response to Digital Distribution: Recorded Music and Live Performances," Draft, December 29, 2005.
- Oberholzer, Felix and Koleman Strumpf, "The Effect of File Sharing on Record Sales: An Empirical Analysis," Draft, March 2004.
- Owen, Bruce M. and Steven S. Wildman, *Video Economics*, Cambridge: Harvard University Press, 1992.
- Rein, I., "Rudy's Red Wagon," *Communications Strategies in Contemporary Society* 88, 1972.
- Rob, Rafael and Joel Waldfogel, "Piracy on the High C's: Music Downloading, Sales Displacement, and Social Welfare in a Sample of College Students," *Journal of Law and Economics*, Vol. XLIX (April 2006), pp. 29-62.

Rosen, Harvey S., *Public Finance*, 4<sup>th</sup> Edition, Irwin Press, 1995.

Rubin, D.B., *Multiple Imputation for Nonresponse in Surveys*, New York: John Wiley & Sons, Inc., 1987.

Sidak, J. Gregory, and David E. Kronemyer, "The 'New Payola' and the American Record Industry: Transactions Costs and Precautionary Ignorance in Contracts for Illicit Services," *Harvard Journal of Law and Public Policy*, p. 521, 1987.

Spence, A. M. and B. M. Owen, "Television Programming, Monopolistic Competition and Welfare," *Quarterly Journal of Economics* 91:103-126, 1977.

Steiner, Peter O., "Program Patterns and Preferences, and the Workability of Competition in Radio Broadcasting," *Quarterly Journal of Economics*, 66: 194-223, 1952.

Sweeting, Andrew, "Too Much Rock and Roll? Station Ownership, Programming and Listenership in the Music Radio Industry," Northwestern University, January 15, 2006.

## ***Appendix A: Options in Dealing with Measurement Error***

In this appendix, we analyze the implications of alternative estimation methodologies in the presence of measurement errors and other data issues. The purpose of this exercise was to demonstrate that the optimal regression strategy depends on a multiplicity of factors, including the source and patterns of measurement error, correlations with other sources of error, and relationships with variables that are included and those that are omitted from the regression model. Such factors have to be considered and, to the extent possible, evaluated for their empirical relevance, before settling on a strategy.

A data set was randomly generated for 99 hypothetical market areas for two years of data ( $t = 1, 2$ ). The population distribution was identical to the top 99 DMAs in 2006. The mean population was 2,550 (in thousands) and the standard deviation was 2,650. For each DMA a population weight  $w_i$  was set equal to the percent of total population attributed to that DMA. The range was .004 (or .4 percent) to a high of .07 (or 7.0 percent). The average, since there were 99 DMAs, was .01. Population was assumed to grow at an average rate of four percent over the two time periods. For each DMA the growth was randomly drawn from a normal distribution with a mean of .04 and standard deviation of .01, i.e.,  $[dP_i/P_i = N(\mu, \sigma) = N(.04, .01)]$ .

Recording sales in a given DMA in time period  $t$  was assumed given by the following “true” relationship:

$$(1) \quad S_{it} = .1 + .99R_{it} + .0001P_{it} - .3T_t + u_{it}$$

Where  $S_{it}$  represents sales, .1 is an intercept,  $R_{it}$  are local radio ratings,  $P_{it}$  is DMA population,  $T_t$  is a dummy variable given a value of one for the second panel year and  $u_{it}$  is a disturbance term with characteristics described below.

The disturbance term is assumed to be distributed normally with a mean of zero and standard deviation of  $.5m_u$  where  $m_u$  is a multiplier that increases the degree to which unknown or unobserved factors affect sales.

In addition, disturbances can be serially correlated, allow for the possibility that some of these characteristics are fixed or changing slowly over time. In other words,

$$(2) \quad u_{it} = (p_u u_{it-1} + (1 - p_u) e_{it}) / (p_u^2 + (1 - p_u)^2)^{.5}$$

the degree of serial correlation is determined by the value of  $p_u$ , which takes on a value of between zero and one (one indicates complete correlation, zero none at all). The term  $e_{it}$  is the portion of the total disturbance term that is entirely random and independently distributed  $N(0, .5m_u)$ . Note that the correlation coefficient  $C(u_{it}, u_{it-1}) = \sqrt{p_u}$ , division of the weighted sum by  $(p_u^2 + (1-p_u)^2)$ , preserves the standard deviation of the disturbance. That is,  $u_{it}$  will also be distributed  $N(0, .5m_u)$ .

As one additional set of scenarios to explore, we posited a correlation between the population,  $P_{it}$ , and the error term,  $u_{it}$ . The source of this could be variables for which no data are available that are correlated with population. To model this, we assume that a portion of true population is unavailable so that the observed population is given by  $P^*_{it} = m_p P_{it}$ .

The ratings  $R_{it}$  were also assumed to be drawn from a normal distribution with a mean value of .025 and standard deviation of .005. Given the assumed parameters of the model, this implies average sales of about 2.5.

Ratings data were also generated under three additional sets of scenarios. The first posits measurement error for  $R_{it}$ . This measurement error is assumed to be correlated with the size of the DMA market ( $P_i$ ). This error is given by  $me_{it} = m_e(\mathbf{w}/w_i)\epsilon_{it}$  where  $m_e$  is a multiplier indicating the magnitude of the measurement error,  $w_i$  is the population weight as defined above, and  $\mathbf{w}$  is a scale adjustment (set equal to .006587) to guarantee that the average of the scaled weights ( $\Sigma(\mathbf{w}/w_i) = 1$ , thereby having a neutral effect on the sample standard deviation of the measurement error (but not the distribution across DMA sizes).<sup>54</sup>

The random portion of the measurement error  $\epsilon_{it}$  is distributed  $N(0, .005)$ . Thus, observed ratings  $R^*$  are given by actual ratings plus measurement error, or

$$(3) \quad R_{it}^* = R_{it} + me_{it} = R_{it} + m_e(\mathbf{w}/w_i)\epsilon_{it}$$

---

<sup>54</sup> This specification of measurement error yields a correlation of about -.4 with the population measure. As reported in Liebowitz (2007), the correlation between population and DMA “coverage,” a measure of the degree to which DMA populations are represented by MSAs is .44. Liebowitz implicitly assumes, but does not verify, that coverage is inversely related to measurement error so the alternative characterizations are equivalent.

In addition to the systematic time-series correlation of the standard error of measurement error, we also allowed for year-to-year correlation in the sign of the error. That is,

$$(4) \quad me_{it} = (p_e me_{it-1} + (1 - p_e)m_{it}) / (p_e^2 + (1 - p_e)^2)^{.5}$$

As in the case of serial correlation specified in equation two, this specification allows for serial correlation in the measurement error. The parameter  $p_e$  takes on a value between zero and one with zero indicating no correlation. Dividing by the square root of the sum of the squared weighting parameters preserves the mean and standard error of the measurement, zero and  $.005m_e$ , respectively.

We also allow for both actual ratings to be correlated with population and over time, independent of population.

$$(5) \quad R_{it} = r_{it} (1 + c_{rp}(w_i - .01))$$

As before,  $R_{it}$  represents actual ratings,  $r_{it}$  is drawn from a normal distribution where  $N(.025, .005)$ ,  $c_{rp}$  is a multiplier denoting the strength of the correlation between ratings and DMA population as expressed by the deviation of the DMA weight,  $w_i$ , from its mean value,  $.01$ . Note that for  $c_{rp} = 1$ , expected ratings for the largest DMA (with a weight of  $.07$ ) would be six percent larger than the average DMA. However, across all DMA's the correlation coefficient would only be  $.09$ . At a value of  $c_{rp} = 8$ , the correlation between population and ratings rises to  $.40$ .

We also allow for systematic differences in markets (having nothing to do with observed population) by specifying that ratings are correlated over time. That is,

$$(6) \quad R_{it} = [p_r R_{it-1} + (1 - p_r)r_{it} (1 + c_{rp}(w_i - .01))] / [p_r^2 + (1 - p_r)^2]^{.5}$$

Finally, a subset of simulations assumes that a key variable, in this case,  $P_{it}$ , is a "left-out variable," (LOV). When LOV is set = 1, population is excluded from the analysis. Table B.1 summarizes the key parameters used to generate alternative data sets for simulations. Table B.2 provides specific parameter values for each of 14 sets of simulated data.

Table A.1  
Simulation Parameters

$m_e$	Scale factor indicating the magnitude of measurement error in observing ratings (assumed to be inversely correlated with population)
$C_{rp}$	Factor indicating correlation between ratings and population $C(r_t, p_t)$
$p_r$	Factor indicating serial correlation in ratings, true correlation $C(r_t, r_{t-1})$
$P_u$	Factor indicating serial correlation in regression residuals $C(u_t, u_{t-1})$
$P_e$	Factor represents serial correlation in measurement error $C(m_{e_t}, m_{e_{t-1}})$
$m_u$	Scaling factor altering size of the standard deviation of regression residual, $\sigma_u = .005 m_u$
LOV	LOV = 1 (0 otherwise ) indicates the presence of missing variables, in this case $P_{it}$

Table A.2  
Alternative Scenarios for Data Simulation

Scenario	Description	Parameter Values						
		$m_u$	$m_e$	$C_{rp}$	$p_r$	$p_e$	$p_u$	LOV
1	Small, "well-behaved" residuals	1	0	0	0	0	0	0
2	Large, "well-behaved" residuals	5	0	0	0	0	0	0
3	Small residuals, modest measurement error	1	1	0	0	0	0	0
4	Small residuals, large measurement error	1	2	0	0	0	0	0
5	Small, "well-behaved" residuals, negative correlation between covariates	1	0	-8	0	0	0	0
6	Small residuals, negative correlation between included and "left-out" variables	1	0	-8	0	0	0	1
7	Small, "well-behaved" residuals, positive correlation between covariates	1	0	8	0	0	0	0
8	Small residuals, positive correlation between included and "left-out" covariates	1	0	8	0	0	0	1
9	Large residuals, modest measurement error	5	1	0	0	0	0	0
10	Small "well-behaved" residuals, positive correlation in ratings	1	0	0	0.75	0	0	0

11	Small residuals, modest measurement error and serially correlated measurement error	1	1	0	0	0.75	0	0
12	Small residuals, serial correlation in regression error	1	0	0	0	0	0.75	0
13	Small residuals, modest measurement error, positive correlation between included and "left-out" covariates	1	1	8	0.75	0	0	1
14	Large residuals, positive correlation between included covariates	5	0	8	0	0	0	0

As we have seen, the data will vary as a function of a variety of assumptions regarding the distribution of regression (the  $u_t$ 's), measurement error in ratings (the  $me_t$ 's). Key factors include the standard deviations in errors, serial correlations, and correlations among residuals and explanatory variables. Models were then estimated using four alternative estimation strategies. The first two used the complete sample of 99 DMAs. OLS regressions were employed in either levels or first differences where both dependent and independent variables were expressed as changes from year one to year two. The second two used truncated samples as a potential remedy for measurement error that, for some data scenarios, was assumed to be more pronounced for smaller DMAs. Thus, the 60 largest DMAs were used in the regressions.

Table A.3  
Alternative Estimation Strategies

Estimation Strategy	Description
A	Levels, full sample
B	Differences, full sample
C	Levels, truncated sample
D	Differences, truncated sample

Key outcomes for each of these regressions are reported in Table A.4. This table shows the  $R^2$  statistic, as well as the coefficient, standard error, and t-statistic for the key variable of interest, the effect of radio ratings on recording sales. Recall that, by assumption, the true coefficient is equal to 100.



The results of the simulations make it clear that the correct choice of a regression strategy depends on a multitude of factors that are not generally known in advance (or in some cases, ever). If the goal is to obtain an accurate and unbiased estimated of a particular coefficient, the optimal approach depends on the structure and patterns of the data, the regression residuals, and measurement error. In cases when the model is well-specified and the data are “well-behaved,” the choice of models is largely irrelevant. In fact, comparisons of results from different methods has been suggested as a valuable test

Table A.4  
Simulated Regression Results

Scenario	Strategy	R <sup>2</sup>	Coeff.	S.E.	t-statistic
1	A	0.68	99.37	8.19	12.14
1	B	0.46	96.33	10.47	9.19
2	A	0.09	96.85	40.94	2.37
2	B	0.05	81.70	52.36	1.56
3	A	0.58	63.87	6.86	9.31
3	B	0.21	40.95	7.81	5.24
4	A	0.44	34.46	5.35	6.45
4	B	0.11	17.31	5.19	3.33
4	C	0.49	48.82	8.87	5.50
4	D	0.14	27.24	8.12	3.35
5	A	0.62	99.61	8.14	12.24
5	B	0.46	97.69	10.53	9.28
6	A	0.42	80.61	9.49	8.49
6	B	0.44	95.03	10.64	8.93
7	A	0.76	99.13	8.21	12.08
7	B	0.45	95.06	10.36	9.17
8	A	0.64	121.90	9.23	13.20
8	B	0.44	91.77	10.41	8.81
9	A	0.11	84.95	29.36	2.89
9	B	0.01	27.38	32.62	0.84
10	A	0.55	96.92	12.23	7.92
10	B	0.05	85.36	41.89	2.04
11	A	0.47	51.50	7.24	7.12
11	B	0.45	90.10	9.89	9.11
12	A	0.56	97.30	10.20	9.54
12	B	0.96	100.29	2.10	47.81
13	A	0.21	56.73	10.85	5.23
13	B	-0.07	4.58	8.85	0.51

14	A	0.13	95.67	41.04	2.33
14	B	0.02	75.32	51.82	1.45
14	C	0.14	91.75	52.28	1.75
14	D	0.03	37.98	58.32	0.65

to identify potential problems. However, under different scenarios, different strategies emerge as most preferred.

When regression residuals are large, often indicated by a low  $R^2$ , differencing is not generally a good strategy because the “signal to noise” ratio declines after differencing. This is especially the case when there is serial correlation in the level of covariates. By differencing, one loses much of the variation in explanatory variables, thereby diminishing the precision of the estimates. On the other hand, when errors are correlated, such as in the scenarios that assume the existence of a left-out variable that is correlated with an included variable or when measurement errors are serially correlated (such as scenario six and 11), the amount of error is reduced with differencing.

In theory, using a truncated sample involves “throwing away” potentially useful information, thereby reducing efficiency of estimation and generally increasing standard errors of coefficient estimates. Under a wide range of scenarios, this is not an effective strategy. On the other hand, if significant measurement error exists and its pattern is systematic and known a priori, there may be some circumstances under which truncation reduces bias sufficiently to justify the attendant loss in efficiency. In one of our 14 simulated data sets, scenario four, truncation of data resulted in the most accurate estimate of the key coefficient. Scenario four is characterized by significant measurement error but other regression errors are small and well-behaved and the model is otherwise specified with precision. It is worth noting that, under such conditions, the levels model out performs the differences model using truncated data. Indeed, the levels model using the full sample would be preferred to the difference model using truncated data. Although there are likely circumstances under which both differencing and truncation would be advisable (such as large fixed effects as well as systemic measurement error), these circumstances would be difficult to identify *ex ante*.

Without detailed examination of actual data, is not possible to determine which circumstances prevail in the sales of albums or tracks/radio airplay listening data sets.

However, it is likely that many of the aforementioned “problems” prevail to some degree. Moreover, it is clear that the explanatory power of the models utilized is not high and the drop in  $R^2$ , after differencing is substantial. Given that the magnitude and pattern of hypothesized measurement error due to inconsistencies in the match between MSAs, radio markets and DMA remains unknown, the presence of these other factors would cast some doubt on the appropriate choice of methods.

Table A.5  
Summary of Simulated Regression Results

Scenario	Description	Dominant Strategy
1	Small, "well-behaved" residuals	A,B
2	Large, "well-behaved" residuals	A
3	Small residuals, modest measurement error	A
4	Small residuals, large measurement error	C
5	Small, "well-behaved" residuals, negative correlation between covariates	A,B
6	Small residuals, negative correlation between included and "left-out" variables	B
7	Small, "well-behaved" residuals, positive correlation between covariates	A,B
8	Small residuals, positive correlation between included and "left-out" covariates	B
9	Large residuals, modest measurement error	A
10	Small "well-behaved" residuals, positive correlation in ratings	A
11	Small residuals, modest measurement error and serially correlated measurement error	B
12	Small residuals, serial correlation in regression error	A,B
13	Small residuals, modest measurement error, positive correlation between included and "left-out" covariates	A

14	Large residuals, positive correlation between included covariates	A
----	---	---

**Appendix B: Supplemental Regression Results**

The following represent a series of supplemental analyses conducted to test the sensitivity of empirical findings to alternative methods and data. These are discussed in the Section four of the main report.

Table B.1  
Test of Sensitivity: Actual Ratings

Variable	Log(Albums)		Log(Tracks)		Log(Current)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-13.4458	1.8304	-36.3460	2.2201	-6.3079	1.7547
Actual ratings	2.6249	0.5553	2.2771	0.6736	2.8265	0.5324
year = 2006	-0.1802	0.0173	1.9097	0.0209	-0.2148	0.0165
year = 2005	-0.1117	0.0150	1.3936	0.0182	-0.1308	0.0143
East North Central	0.0525	0.0350	0.0182	0.0425	0.0715	0.0336
East South Central	0.0847	0.0375	-0.0206	0.0455	0.0447	0.0360
Middle Atlantic	0.1623	0.0502	0.2446	0.0609	0.1424	0.0482
Mountain	0.1505	0.0454	0.1426	0.0551	0.0828	0.0436
Pacific	0.2175	0.0634	0.2764	0.0769	0.1747	0.0608
South Atlantic	0.0707	0.0406	0.1099	0.0493	0.0917	0.0389
West North Central	0.0108	0.0290	0.1033	0.0351	0.0090	0.0278
West South Central	0.0086	0.0377	0.0391	0.0457	0.0137	0.0361
log(population 12+)	0.6712	0.1896	1.3290	0.2300	0.6891	0.1818
% Asian	-0.6941	0.5327	-1.0713	0.6462	-0.7657	0.5107
% African American	0.2455	0.1356	-0.2501	0.1645	0.2322	0.1300
% Hispanic	-0.0506	0.1213	0.1524	0.1471	-0.0512	0.1163
% Age 18-24	2.5965	1.4935	10.6274	1.8115	1.6823	1.4317
% Age 25-34	0.1903	1.4349	3.0621	1.7405	1.0559	1.3756
% Age 35-44	2.4119	2.5175	9.1917	3.0536	1.2999	2.4134
% Age 45-54	2.1202	1.8669	7.1904	2.2645	0.9728	1.7897
% Age 55-64	3.8765	2.1077	2.2161	2.5565	3.5684	2.0205

Table B.1 (continued)  
 Test of Sensitivity: Actual Ratings

Variable	Log(Albums)		Log(Tracks)		Log(Current)	
	Coefficient	Standard Error	Coefficient	Variable	Coefficient	Standard Error
% Age 65+	-0.2007	1.0503	5.1147	1.2739	-0.6022	1.0068
log(Web)	0.4948	0.2184	-0.1743	0.2649	0.4452	0.2094
log(DSL)	-0.1791	0.0364	-0.1145	0.0442	-0.1449	0.0349
log(Cable)	-0.1376	0.0359	0.0571	0.0436	-0.1242	0.0344
log(Web Media)	0.1299	0.0905	-0.0591	0.1097	0.1104	0.0867
log(hourly earnings)	-0.0402	0.1125	-0.1540	0.1364	-0.0071	0.1078
log(commute)	-0.1340	0.1199	0.3967	0.1454	-0.1681	0.1149
log(income)	0.4961	0.1319	1.5071	0.1600	0.5348	0.1264
log(unemployment rate)	-0.1081	0.0448	-0.2337	0.0544	-0.0857	0.0430
log(retail wage)	0.2866	0.1792	0.7929	0.2173	0.1889	0.1718
% Retail employment	-3.5829	0.9440	-0.7782	1.1450	-3.7057	0.9050
% Construction	0.9403	0.3825	-0.5503	0.4639	0.9402	0.3666
% Food Services	6.7357	1.3663	1.7553	1.6572	6.4318	1.3098
% Manufacturing	-1.1502	0.2063	-0.8846	0.2502	-1.0852	0.1978
% Health Care	-0.5941	0.5846	0.8435	0.7091	-0.2391	0.5604

Table B.2  
Tests of Sensitivity: Actual Ratings (Predicted)

Variable	Log(Albums)		Log(Tracks)		Log(Current)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-11.2956	1.8230	-34.4248	2.1807	-4.0119	1.7612
Actual ratings, predicted	1.2820	0.3468	1.3147	0.4149	1.3106	0.3351
year = 2006	-0.1771	0.0176	1.9134	0.0211	-0.2118	0.0170
year = 2005	-0.1117	0.0152	1.3940	0.0182	-0.1310	0.0147
East North Central	0.0323	0.0354	0.0004	0.0423	0.0498	0.0342
East South Central	0.0681	0.0383	-0.0372	0.0458	0.0275	0.0370
Middle Atlantic	0.1129	0.0490	0.2055	0.0586	0.0879	0.0473
Mountain	0.1696	0.0459	0.1583	0.0549	0.1037	0.0444
Pacific	0.1586	0.0620	0.2304	0.0742	0.1095	0.0599
South Atlantic	0.0276	0.0409	0.0707	0.0489	0.0459	0.0395
West North Central	0.0040	0.0293	0.0989	0.0351	0.0012	0.0284
West South Central	-0.0329	0.0374	0.0025	0.0448	-0.0309	0.0362
log(population 12+)	0.4231	0.1860	1.1119	0.2225	0.4226	0.1797
% Asian	-0.4127	0.5371	-0.8358	0.6424	-0.4598	0.5188
% African American	0.2756	0.1375	-0.2360	0.1645	0.2687	0.1329
% Hispanic	0.1219	0.1122	0.2875	0.1342	0.1396	0.1084
% Age 18-24	3.3155	1.5132	11.2688	1.8101	2.4504	1.4619
% Age 25-34	-0.6430	1.4356	2.4304	1.7173	0.1271	1.3869
% Age 35-44	2.7238	2.5600	9.4910	3.0623	1.6259	2.4732
% Age 45-54	2.5981	1.8945	7.5913	2.2662	1.4920	1.8302
% Age 55-64	5.4254	2.1611	3.7324	2.5852	5.1767	2.0878
% Age 65+	-0.4906	1.0664	4.8597	1.2756	-0.9131	1.0302
log(Web)	0.7129	0.2172	0.0155	0.2599	0.6798	0.2099
log(DSL)	-0.2039	0.0374	-0.1391	0.0447	-0.1705	0.0361
log(Cable)	-0.1354	0.0366	0.0562	0.0438	-0.1208	0.0353
log(Web Media)	0.1878	0.0934	0.0008	0.1118	0.1695	0.0903
log(hourly earnings)	-0.1638	0.1131	-0.2666	0.1353	-0.1382	0.1093
log(commute)	0.0274	0.1186	0.5408	0.1418	0.0042	0.1145
log(income)	0.3873	0.1328	1.4098	0.1588	0.4186	0.1283
log(unemployment rate)	-0.1238	0.0458	-0.2497	0.0547	-0.1018	0.0442
log(retail wage)	0.1437	0.1840	0.6529	0.2201	0.0405	0.1778
% Retail employment	-3.4156	0.9598	-0.6217	1.1481	-3.5294	0.9272
% Construction	1.2459	0.3763	-0.3237	0.4501	1.2825	0.3635
% Food Services	6.5073	1.3889	1.5467	1.6614	6.1895	1.3417
% Manufacturing	-0.8110	0.2041	-0.5764	0.2441	-0.7247	0.1972
% Health Care	-1.2040	0.5726	0.3394	0.6849	-0.9044	0.5532

Table B.3  
 Test of Sensitivity: Actual Music Exposures

Variable	Log(Albums)		Log(Tracks)		Log(Current)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-12.5895	1.7706	-35.5482	2.1734	-5.2907	1.7145
Actual exposures	0.0232	0.0042	0.0188	0.0051	0.0226	0.0040
year = 2006	-0.1932	0.0171	1.8990	0.0210	-0.2278	0.0165
year = 2005	-0.1178	0.0147	1.3884	0.0181	-0.1371	0.0143
East North Central	0.0514	0.0344	0.0162	0.0422	0.0685	0.0333
East South Central	0.0682	0.0370	-0.0342	0.0454	0.0282	0.0358
Middle Atlantic	0.1470	0.0482	0.2279	0.0591	0.1201	0.0467
Mountain	0.1369	0.0450	0.1331	0.0552	0.0721	0.0435
Pacific	0.1676	0.0599	0.2307	0.0735	0.1168	0.0580
South Atlantic	0.0752	0.0400	0.1118	0.0491	0.0930	0.0387
West North Central	0.0120	0.0285	0.1033	0.0350	0.0085	0.0276
West South Central	0.0006	0.0366	0.0304	0.0450	0.0020	0.0355
log(population 12+)	0.6164	0.1830	1.2709	0.2247	0.6118	0.1772
% Asian	-0.0411	0.5229	-0.5235	0.6418	-0.0948	0.5063
% African American	0.2488	0.1330	-0.2412	0.1632	0.2461	0.1288
% Hispanic	0.1246	0.1071	0.3097	0.1315	0.1465	0.1037
% Age 18-24	3.7558	1.4680	11.6008	1.8020	2.8748	1.4215
% Age 25-34	0.0397	1.4000	2.8577	1.7186	0.7661	1.3557
% Age 35-44	3.2076	2.4808	9.8430	3.0452	2.0893	2.4022
% Age 45-54	2.9372	1.8345	7.8843	2.2519	1.8268	1.7764
% Age 55-64	3.3938	2.0794	1.8523	2.5525	3.1437	2.0136
% Age 65+	0.5899	1.0498	5.7385	1.2886	0.1419	1.0165
log(Web)	0.6327	0.2108	-0.0502	0.2587	0.6014	0.2041
log(DSL)	-0.1737	0.0359	-0.1105	0.0440	-0.1401	0.0347
log(Cable)	-0.1556	0.0358	0.0437	0.0439	-0.1397	0.0346
log(Web Media)	0.0356	0.0906	-0.1354	0.1112	0.0182	0.0877
log(hourly earnings)	0.0097	0.1120	-0.1188	0.1375	0.0327	0.1084
log(commute)	-0.1717	0.1187	0.3741	0.1457	-0.1912	0.1150
log(income)	0.4058	0.1285	1.4287	0.1577	0.4375	0.1244
log(unemployment rate)	-0.1234	0.0442	-0.2462	0.0543	-0.1007	0.0428
log(retail wage)	0.2781	0.1763	0.7836	0.2164	0.1763	0.1707
% Retail employment	-2.2667	0.9546	0.2921	1.1718	-2.4120	0.9244
% Construction	0.7607	0.3819	-0.6633	0.4688	0.8206	0.3698
% Food Services	4.6541	1.3882	0.0620	1.7040	4.3847	1.3442
% Manufacturing	-0.9362	0.1963	-0.6968	0.2410	-0.8511	0.1901
% Health Care	-0.6624	0.5669	0.7433	0.6959	-0.3835	0.5490

Table B.4  
 Test of Sensitivity: Actual Exposures (Predicted)

Variable	Log(Albums)		Log(Tracks)		Log(Current)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-11.5559	1.7398	-34.7034	2.1343	-4.2847	1.6914
Actual exposures, predicted	0.0238	0.0039	0.0214	0.0047	0.0226	0.0037
year = 2006	-0.1899	0.0168	1.9011	0.0206	-0.2244	0.0163
year = 2005	-0.1183	0.0145	1.3877	0.0178	-0.1374	0.0141
East North Central	0.0557	0.0340	0.0216	0.0417	0.0721	0.0330
East South Central	0.0595	0.0366	-0.0432	0.0449	0.0202	0.0356
Middle Atlantic	0.1551	0.0476	0.2405	0.0585	0.1263	0.0463
Mountain	0.1471	0.0441	0.1387	0.0541	0.0828	0.0429
Pacific	0.1779	0.0593	0.2437	0.0727	0.1255	0.0576
South Atlantic	0.0608	0.0391	0.1021	0.0480	0.0784	0.0380
West North Central	0.0117	0.0281	0.1046	0.0344	0.0078	0.0273
West South Central	-0.0017	0.0360	0.0311	0.0442	-0.0009	0.0350
log(population 12+)	0.4699	0.1778	1.1555	0.2182	0.4679	0.1729
% Asian	0.0661	0.5177	-0.3982	0.6350	-0.0012	0.5032
% African American	0.2857	0.1304	-0.2173	0.1600	0.2839	0.1268
% Hispanic	0.1374	0.1053	0.3130	0.1291	0.1610	0.1023
% Age 18-24	4.2608	1.4559	12.1053	1.7860	3.3401	1.4154
% Age 25-34	-0.4446	1.3695	2.5364	1.6801	0.2736	1.3314
% Age 35-44	4.1062	2.4591	10.7119	3.0167	2.9254	2.3906
% Age 45-54	2.5049	1.8105	7.5184	2.2211	1.4098	1.7602
% Age 55-64	5.2271	2.0509	3.4166	2.5160	4.9091	1.9939
% Age 65+	0.5027	1.0311	5.7562	1.2649	0.0317	1.0024
log(Web)	0.7494	0.2077	0.0479	0.2548	0.7142	0.2019
log(DSL)	-0.1762	0.0354	-0.1118	0.0434	-0.1428	0.0344
log(Cable)	-0.1439	0.0349	0.0508	0.0428	-0.1276	0.0339
log(Web Media)	0.0699	0.0884	-0.1129	0.1084	0.0531	0.0859
log(hourly earnings)	-0.0218	0.1091	-0.1345	0.1339	-0.0009	0.1061
log(commute)	-0.1186	0.1148	0.4062	0.1408	-0.1363	0.1116
log(income)	0.3397	0.1272	1.3693	0.1561	0.3747	0.1237
log(unemployment rate)	-0.1325	0.0437	-0.2556	0.0537	-0.1090	0.0425
log(retail wage)	0.1867	0.1741	0.7044	0.2136	0.0887	0.1693
% Retail employment	-2.4031	0.9337	0.2802	1.1454	-2.5730	0.9077
% Construction	0.7291	0.3749	-0.7580	0.4599	0.8095	0.3645
% Food Services	4.9203	1.3539	0.1272	1.6609	4.6872	1.3162
% Manufacturing	-0.7624	0.1950	-0.5438	0.2392	-0.6850	0.1895
% Health Care	-0.8104	0.5529	0.6737	0.6783	-0.5421	0.5375



Table B.5  
 Tests of Sensitivity: Imputed Values, (Predicted  $m_1$ )

Variable	Log(Albums)		Log(Tracks)		Log(Current)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-12.9050	1.8559	-36.3611	2.1976	-5.5666	1.8005
Exposures, predicted* ( $m_1$ )	0.0113	0.0038	0.0130	0.0045	0.0110	0.0037
year = 2006	-0.1911	0.0179	1.8980	0.0213	-0.2258	0.0173
year = 2005	-0.1228	0.0156	1.3816	0.0185	-0.1419	0.0151
East North Central	0.0422	0.0358	0.0115	0.0426	0.0595	0.0347
East South Central	0.0734	0.0386	-0.0326	0.0459	0.0333	0.0374
Middle Atlantic	0.1250	0.0505	0.2223	0.0600	0.0987	0.0489
Mountain	0.1588	0.0466	0.1452	0.0555	0.0934	0.0452
Pacific	0.1768	0.0642	0.2552	0.0764	0.1258	0.0622
South Atlantic	0.0442	0.0412	0.0883	0.0490	0.0627	0.0399
West North Central	0.0174	0.0305	0.1154	0.0363	0.0138	0.0295
West South Central	-0.0295	0.0378	0.0060	0.0449	-0.0274	0.0366
log(population 12+)	0.5205	0.1899	1.2222	0.2259	0.5182	0.1840
% Asian	-0.5759	0.5468	-1.0294	0.6502	-0.6167	0.5297
% African American	0.2951	0.1386	-0.2228	0.1648	0.2912	0.1343
% Hispanic	0.1114	0.1156	0.2643	0.1375	0.1335	0.1120
% Age 18-24	2.3685	1.5525	10.1965	1.8463	1.5207	1.5042
% Age 25-34	-1.2526	1.4405	1.8015	1.7131	-0.4946	1.3956
% Age 35-44	1.9385	2.5914	8.6125	3.0818	0.8507	2.5108
% Age 45-54	2.2590	1.9174	7.1921	2.2803	1.1649	1.8578
% Age 55-64	3.5893	2.1752	1.7594	2.5868	3.3338	2.1075
% Age 65+	-0.6899	1.0789	4.6285	1.2831	-1.1067	1.0453
log(Web)	0.6062	0.2220	-0.1063	0.2640	0.5755	0.2151
log(DSL)	-0.2007	0.0378	-0.1379	0.0449	-0.1665	0.0366
log(Cable)	-0.1144	0.0366	0.0780	0.0435	-0.0995	0.0355
log(Web Media)	0.1644	0.0937	-0.0187	0.1114	0.1438	0.0908
log(hourly earnings)	-0.1202	0.1138	-0.2208	0.1354	-0.0940	0.1103
log(commute)	0.0423	0.1203	0.5611	0.1430	0.0176	0.1165
log(income)	0.4370	0.1343	1.4645	0.1598	0.4679	0.1302
log(unemployment rate)	-0.1198	0.0462	-0.2468	0.0549	-0.0972	0.0447
log(retail wage)	0.2549	0.1837	0.7683	0.2185	0.1538	0.1780
% Retail employment	-3.8252	0.9752	-1.0827	1.1597	-3.9326	0.9448
% Construction	1.3584	0.3765	-0.2243	0.4478	1.4036	0.3648
% Food Services	7.0220	1.4098	2.1289	1.6766	6.6950	1.3659
% Manufacturing	-0.8278	0.2060	-0.5851	0.2449	-0.7452	0.1996
% Health Care	-1.2220	0.5782	0.3378	0.6877	-0.9293	0.5602

Table B.6  
 Tests of Sensitivity: Imputed Values (Predicted  $m_2$ )

Variable	Log(Albums)		Log(Tracks)		Log(Current)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-12.9050	1.8559	-36.3611	2.1976	-5.5666	1.8005
Exposures, predicted $m_2$	0.0103	0.0029	0.0129	0.0034	0.0098	0.0028
year = 2006	-0.1681	0.0180	1.9260	0.0214	-0.2037	0.0175
year = 2005	-0.1071	0.0154	1.4004	0.0182	-0.1268	0.0149
East North Central	0.0177	0.0357	-0.0184	0.0423	0.0360	0.0346
East South Central	0.0676	0.0384	-0.0408	0.0455	0.0279	0.0372
Middle Atlantic	0.0841	0.0487	0.1748	0.0576	0.0589	0.0472
Mountain	0.1726	0.0460	0.1607	0.0544	0.1069	0.0446
Pacific	0.1471	0.0617	0.2233	0.0731	0.0963	0.0599
South Atlantic	0.0392	0.0408	0.0824	0.0483	0.0578	0.0396
West North Central	-0.0065	0.0293	0.0879	0.0347	-0.0095	0.0284
West South Central	-0.0125	0.0378	0.0272	0.0447	-0.0112	0.0366
log(population 12+)	0.4357	0.1862	1.1251	0.2205	0.4355	0.1807
% Asian	-0.5988	0.5417	-1.0813	0.6414	-0.6328	0.5255
% African American	0.2656	0.1383	-0.2657	0.1637	0.2647	0.1341
% Hispanic	0.0843	0.1153	0.2194	0.1365	0.1105	0.1118
% Age 18-24	3.7617	1.5228	11.8535	1.8032	2.8663	1.4773
% Age 25-34	-0.9337	1.4311	2.1978	1.6947	-0.1907	1.3884
% Age 35-44	2.7477	2.5636	9.5624	3.0356	1.6354	2.4870
% Age 45-54	2.9523	1.8983	8.0156	2.2479	1.8348	1.8417
% Age 55-64	5.4989	2.1679	4.0735	2.5671	5.1677	2.1032
% Age 65+	-0.3548	1.0682	5.0249	1.2649	-0.7825	1.0363
log(Web)	0.7156	0.2175	0.0198	0.2576	0.6821	0.2110
log(DSL)	-0.1956	0.0372	-0.1332	0.0440	-0.1612	0.0361
log(Cable)	-0.1223	0.0363	0.0683	0.0430	-0.1071	0.0352
log(Web Media)	0.1609	0.0926	-0.0191	0.1096	0.1396	0.0898
log(hourly earnings)	-0.1730	0.1136	-0.2861	0.1345	-0.1445	0.1102
log(commute)	0.0732	0.1202	0.6042	0.1423	0.0459	0.1166
log(income)	0.4307	0.1330	1.4601	0.1575	0.4611	0.1291
log(unemployment rate)	-0.0986	0.0458	-0.2214	0.0542	-0.0768	0.0444
log(retail wage)	0.2659	0.1823	0.7831	0.2159	0.1639	0.1768
% Retail employment	-3.5577	0.9611	-0.7835	1.1380	-3.6696	0.9324
% Construction	1.4472	0.3711	-0.1271	0.4395	1.4914	0.3601
% Food Services	6.5188	1.3907	1.5460	1.6467	6.2052	1.3491
% Manufacturing	-0.7509	0.2071	-0.4810	0.2452	-0.6740	0.2009
% Health Care	-1.2763	0.5722	0.2848	0.6776	-0.9845	0.5551

Table B.7  
Tests of Sensitivity: Log Model

Variable	Log(Albums)		Log(Tracks)		Log(Current)		Log(Catalog)		Log(Urban)		Log(Country)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-14.2423	1.9187	-37.5800	2.2928	-6.8569	1.8610	-8.3549	2.1591	-6.9371	2.7596	-5.2552	2.2198
log(exposures)	0.1411	0.0346	0.1520	0.0414	0.1351	0.0336	0.0539	0.0159	0.0061	0.0017	0.2171	0.0221
year = 2006	-0.1646	0.0180	1.9272	0.0215	-0.2002	0.0175	-0.1081	0.0209	-0.4327	0.0254	-0.0706	0.0206
year = 2005	-0.1050	0.0153	1.4014	0.0183	-0.1247	0.0148	-0.0730	0.0179	-0.1718	0.0220	-0.0526	0.0178
East North												
Central	0.0138	0.0355	-0.0197	0.0424	0.0322	0.0344	-0.0037	0.0415	-0.0102	0.0523	0.1105	0.0433
East South												
Central	0.0679	0.0381	-0.0380	0.0455	0.0281	0.0369	0.1367	0.0448	0.0314	0.0554	-0.0676	0.0446
Middle												
Atlantic	0.0709	0.0485	0.1615	0.0580	0.0462	0.0471	0.1159	0.0572	0.1105	0.0742	-0.1190	0.0587
Mountain	0.1770	0.0456	0.1659	0.0545	0.1111	0.0443	0.2938	0.0538	0.1486	0.0667	-0.0739	0.0544
Pacific	0.1363	0.0611	0.2080	0.0730	0.0860	0.0593	0.1984	0.0719	0.1156	0.0893	-0.0503	0.0724
South Atlantic	0.0376	0.0405	0.0808	0.0484	0.0563	0.0393	0.0100	0.0477	0.0229	0.0616	0.0958	0.0500
West North												
Central	-0.0081	0.0291	0.0864	0.0347	-0.0111	0.0282	0.0087	0.0343	0.0176	0.0432	-0.0099	0.0347
West South												
Central	-0.0237	0.0372	0.0122	0.0445	-0.0218	0.0361	-0.0368	0.0438	-0.1317	0.0565	0.1415	0.0460
log(population												
12+)	0.2836	0.1886	0.9611	0.2254	0.2898	0.1830	0.3357	0.2197	0.2549	0.2821	0.4747	0.2267
% Asian	-0.5149	0.5352	-0.9486	0.6395	-0.5542	0.5191	-0.1796	0.6285	0.2585	0.7761	-2.3607	0.6290
% African												
American	0.2877	0.1361	-0.2269	0.1627	0.2852	0.1320	0.3847	0.1593	2.1971	0.1986	-1.2023	0.1652
% Hispanic	0.1185	0.1113	0.2791	0.1329	0.1422	0.1079	0.1420	0.1285	0.6725	0.1599	-0.8869	0.1309
% Age 18-24	3.8642	1.5130	11.8655	1.8080	2.9687	1.4675	5.4621	1.7835	4.5071	2.2303	0.8928	1.7876
% Age 25-34	-1.3941	1.4196	1.6513	1.6963	-0.6295	1.3769	-2.9746	1.6750	-4.6640	2.0859	-1.7204	1.6687
% Age 35-44	2.8885	2.5464	9.6777	3.0428	1.7718	2.4698	4.4359	2.9951	8.4912	3.7140	-7.9408	2.9921
% Age 45-54	2.5907	1.8837	7.5789	2.2510	1.4905	1.8271	4.2709	2.2176	-3.9135	2.7497	3.1915	2.2141
% Age 55-64	5.7787	2.1580	4.1691	2.5787	5.4446	2.0931	6.0040	2.5267	12.1325	3.1003	9.8485	2.5299

% Age 65+	-0.4428	1.0603	4.9100	1.2670	-0.8659	1.0284	0.0731	1.2499	-1.6777	1.5572	-5.5280	1.2603
log(Web)	0.7019	0.2160	0.0039	0.2581	0.6691	0.2095	0.8333	0.2551	0.8508	0.3190	0.2094	0.2576
log(DSL)	-0.1986	0.0370	-0.1345	0.0442	-0.1642	0.0359	-0.2545	0.0436	-0.2306	0.0537	-0.0666	0.0448
log(Cable)	-0.1075	0.0361	0.0852	0.0432	-0.0929	0.0350	-0.1379	0.0424	-0.0511	0.0525	-0.1388	0.0424
log(Web Media)	0.1690	0.0920	-0.0163	0.1100	0.1475	0.0893	0.1566	0.1076	0.0903	0.1360	0.2624	0.1084
log(hourly earnings)	-0.1755	0.1127	-0.2811	0.1347	-0.1472	0.1093	-0.2468	0.1338	-0.1589	0.1678	-0.4241	0.1367
log(commute)	0.1106	0.1207	0.6318	0.1442	0.0823	0.1171	0.1812	0.1445	-0.0820	0.1744	-0.0786	0.1412
log(income)	0.4476	0.1323	1.4737	0.1581	0.4774	0.1284	0.4015	0.1557	0.4022	0.1966	0.6146	0.1566
log(unemploy rate)	-0.1040	0.0454	-0.2290	0.0542	-0.0819	0.0440	-0.1283	0.0536	-0.0407	0.0659	-0.0220	0.0537
log(retail wage)	0.2687	0.1810	0.7823	0.2163	0.1667	0.1756	0.3881	0.2129	0.5283	0.2653	-0.0230	0.2135
% Retail employment	-3.8286	0.9578	-1.0629	1.1445	-3.9296	0.9290	-3.6141	1.1258	-4.2728	1.3984	-3.0228	1.1289
% Construction	1.4921	0.3684	-0.0712	0.4402	1.5340	0.3573	1.5320	0.4345	2.3623	0.5380	0.6560	0.4350
% Food Services	6.8460	1.3825	1.9081	1.6520	6.5181	1.3409	7.4176	1.6268	6.8698	2.0139	5.2545	1.6358
% Manufacturing	-0.7155	0.2065	-0.4691	0.2468	-0.6390	0.2003	-0.9145	0.2407	-0.8827	0.2979	-1.1418	0.2372
% Health Care	-1.2316	0.5686	0.3178	0.6795	-0.9410	0.5515	-1.8560	0.6681	-1.0800	0.8289	-0.0932	0.6685
	R <sup>2</sup>	0.9839	R <sup>2</sup>	0.9918	R <sup>2</sup>	0.9847	R <sup>2</sup>	0.9784	R <sup>2</sup>	0.9724	R <sup>2</sup>	0.9581

Table B.8  
 Test of Sensitivity: Logistic Model

	Log(Albums)		Log(Tracks)	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-13.0866	1.8622	-36.2173	2.2247
Exposures per cap				
μ	0.0300	0.0049	0.0341	0.0059
κ	0.1550	0.0473	0.1497	0.0463
year = 2006	-0.1654	0.0182	1.9249	0.0217
year = 2005	-0.1049	0.0155	1.4001	0.0185
East North Central	0.0119	0.0360	-0.0226	0.0429
East South Central	0.0698	0.0384	-0.0338	0.0458
Middle Atlantic	0.0719	0.0488	0.1627	0.0584
Mountain	0.1772	0.0461	0.1697	0.0551
Pacific	0.1403	0.0617	0.2084	0.0736
South Atlantic	0.0375	0.0408	0.0825	0.0488
West North Central	-0.0108	0.0294	0.0860	0.0351
West South Central	-0.0264	0.0375	0.0100	0.0448
log(population 12+)	0.4736	0.1864	1.1610	0.2230
% Asian	-0.5792	0.5414	-0.9785	0.6473
% African American	0.2583	0.1383	-0.2513	0.1656
% Hispanic	0.1032	0.1134	0.2732	0.1359
% Age 18-24	3.8162	1.5265	11.7154	1.8199
% Age 25-34	-1.2022	1.4372	1.7123	1.7193
% Age 35-44	3.1116	2.5766	9.6960	3.0770
% Age 45-54	2.6720	1.9016	7.7855	2.2702
% Age 55-64	5.3939	2.1634	3.6589	2.5801
% Age 65+	-0.2390	1.0740	5.0213	1.2856
log(Web)	0.6648	0.2177	-0.0298	0.2605
log(DSL)	-0.1924	0.0372	-0.1296	0.0444
log(Cable)	-0.1115	0.0364	0.0798	0.0434
log(Web Media)	0.1524	0.0926	-0.0301	0.1105
log(hourly earnings)	-0.1684	0.1134	-0.2754	0.1355
log(commute)	0.0816	0.1204	0.5996	0.1438
log(income)	0.4442	0.1333	1.4652	0.1592
log(unemployment rate)	-0.1005	0.0457	-0.2269	0.0546
log(retail wage)	0.2880	0.1825	0.8013	0.2181
% Retail employment	-3.8326	0.9759	-1.1627	1.1605
% Construction	1.5448	0.3722	0.0007	0.4437
% Food Services	6.8874	1.4084	2.0988	1.6746
	R <sup>2</sup>	0.9837	R <sup>2</sup>	0.9917

Table B.9  
Separate Estimates by Genre

Variable	Log(Country)		Log(RB)		Log(Rap)		Log(Latin)		Log(Top)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-1.3822	2.4193	-12.1688	2.6441	-12.4553	2.8441	-27.3711	6.5980	-4.9106	1.7363
Exposures per cap (Predicted m <sub>3</sub> )	0.0155	0.0029	0.0113	0.0032	0.0104	0.0034	0.0071	0.0079	0.0082	0.0021
year = 2006	-0.0576	0.0237	-0.4098	0.0259	-0.4208	0.0279	0.0754	0.0648	-0.2407	0.0170
year = 2005	-0.0421	0.0202	-0.1707	0.0220	-0.1400	0.0237	0.0792	0.0550	-0.1560	0.0145
East North Central	0.2062	0.0466	0.0159	0.0509	-0.0088	0.0548	0.4914	0.1271	0.0138	0.0334
East South Central	-0.1078	0.0501	0.0006	0.0548	-0.0289	0.0589	-0.3919	0.1367	-0.0265	0.0360
Middle Atlantic	-0.0034	0.0638	0.1597	0.0697	0.2041	0.0750	0.5174	0.1739	0.0294	0.0458
Mountain Pacific	-0.1686	0.0600	0.1601	0.0655	0.1993	0.0705	-0.0492	0.1635	0.0385	0.0430
South Atlantic	0.0692	0.0804	0.1545	0.0879	0.2011	0.0945	0.5882	0.2192	0.0354	0.0577
West North Central	0.2395	0.0533	0.0848	0.0582	0.0813	0.0626	0.7192	0.1453	0.0534	0.0382
West South Central	0.0435	0.0382	-0.0201	0.0418	-0.0237	0.0449	0.2452	0.1043	-0.0191	0.0274
log(population 12+)	0.2923	0.0490	-0.0504	0.0535	-0.0861	0.0576	0.4501	0.1335	-0.0466	0.0351
% Asian	1.0958	0.2431	0.5403	0.2657	0.6037	0.2857	2.0882	0.6629	0.4856	0.1744
% African American	-3.1699	0.7050	0.1992	0.7705	-0.5308	0.8288	-2.7299	1.9227	-0.6906	0.5060
% Hispanic	-1.7519	0.1789	2.4349	0.1955	1.7922	0.2103	1.0847	0.4878	0.1533	0.1284
% Age 18-24	-1.3521	0.1473	0.5778	0.1610	0.7101	0.1731	3.5435	0.4017	-0.0839	0.1057
% Age 25-34	-0.5213	1.9892	6.5794	2.1741	7.7025	2.3385	-3.3869	5.4250	2.8503	1.4277
% Age 35-44	-0.9065	1.8654	-5.2231	2.0387	-6.3511	2.1929	3.0785	5.0872	-2.7048	1.3388
	-7.7411	3.3493	9.5992	3.6605	11.9837	3.9373	-13.5152	9.1341	2.5993	2.4037

% Age 45-55	3.3770	2.4757	-2.8801	2.7058	-3.6286	2.9104	-11.3609	6.7518	-0.7590	1.7768
% Age 55-64	8.4189	2.8296	13.5912	3.0925	11.8581	3.3264	-11.8020	7.7168	6.7153	2.0307
% Age 65+	-6.9936	1.3953	-0.9474	1.5250	0.1533	1.6403	2.5245	3.8053	-2.1739	1.0014
log(Web)	-0.2420	0.2839	0.6543	0.3103	0.5777	0.3337	-0.6611	0.7742	0.6158	0.2038
log(DSL)	0.0374	0.0484	-0.2118	0.0529	-0.2335	0.0569	-0.0880	0.1320	-0.1271	0.0347
log(Cable)	-0.1401	0.0476	-0.0115	0.0520	-0.0374	0.0559	-0.0008	0.1297	-0.0493	0.0341
log(Web Media)	0.1767	0.1206	0.0057	0.1318	0.0385	0.1417	-0.2421	0.3288	0.0635	0.0865
log(hourly earnings)	-0.1288	0.1478	-0.0674	0.1615	-0.0313	0.1737	-0.3309	0.4031	-0.1845	0.1061
log(commute)	-0.1963	0.1576	0.1386	0.1722	0.1896	0.1852	-1.3905	0.4297	0.0738	0.1131
log(income)	0.4680	0.1738	0.6422	0.1900	0.5291	0.2043	1.4170	0.4741	0.4752	0.1248
log(unemployment rate)	-0.0818	0.0596	-0.0169	0.0651	-0.0879	0.0701	-0.4609	0.1626	-0.0298	0.0428
log(retail wage)	-0.1772	0.2379	0.3833	0.2600	0.5063	0.2796	2.7374	0.6487	0.0625	0.1707
% Retail employment	-2.1670	1.2564	-5.3055	1.3731	-5.0935	1.4769	-4.8725	3.4263	-3.4261	0.9017
% Construction	0.2535	0.4841	2.0933	0.5291	2.3852	0.5691	2.1592	1.3203	1.4741	0.3474
% Food Services	3.5064	1.8154	7.6261	1.9841	7.7834	2.1341	9.7519	4.9509	5.1971	1.3029
% Manufacturing	-0.9699	0.2704	-0.5432	0.2956	-0.3448	0.3179	2.8059	0.7375	-0.6068	0.1941
% Health Care	0.4696	0.7468	-0.4110	0.8162	-1.2386	0.8779	-5.8970	2.0366	-0.4411	0.5359
	R <sup>2</sup>	0.9476	R <sup>2</sup>	0.9740	R <sup>2</sup>	0.9667	R <sup>2</sup>	0.9261	R <sup>2</sup>	0.9846

Table B.10  
Sensitivity Tests: Two-Stage Least Squares

Variable	Log(Exposures) $m_2$		Log(Albums)		Log(Tracks)		Log(Current)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	7.8924	2.9917	-15.4970	2.2466	-38.1110	2.6336	-8.6404	2.1937
log(exposures), $m_2$ predicted	-		0.2489	0.0769	0.2150	0.0901	0.2760	0.0751
year = 2006	0.0789	0.0261	-0.2060	0.0197	1.8874	0.0231	-0.2434	0.0192
year = 2005	0.0731	0.0219	-0.1323	0.0168	1.3758	0.0197	-0.1535	0.0164
East North Central	0.0475	0.0632	0.0477	0.0373	0.0139	0.0437	0.0666	0.0364
East South Central	-0.0289	0.0583	0.0748	0.0400	-0.0292	0.0469	0.0338	0.0391
Middle Atlantic	-0.2801	0.0891	0.1713	0.0569	0.2521	0.0667	0.1548	0.0555
Mountain	-0.0258	0.0745	0.1422	0.0491	0.1356	0.0576	0.0729	0.0480
Pacific	-0.4740	0.0963	0.2515	0.0750	0.3054	0.0879	0.2153	0.0732
South Atlantic	-0.0335	0.0733	0.0696	0.0437	0.1089	0.0512	0.0915	0.0426
West North Central	-0.0198	0.0609	0.0594	0.0366	0.1452	0.0429	0.0634	0.0358
West South Central	0.0293	0.0651	-0.0107	0.0396	0.0223	0.0464	-0.0066	0.0387
Log (population 2+)	0.3072	0.3117	0.4539	0.1949	1.1404	0.2284	0.4558	0.1903
% Asian	0.9036	0.8988	-0.9686	0.5929	-1.3072	0.6951	-1.0810	0.5789
% African American	0.7414	0.2179	0.2053	0.1494	-0.2844	0.1752	0.1842	0.1459
% Hispanic	1.1711	0.1872	-0.0389	0.1387	0.1635	0.1626	-0.0468	0.1354
% Age 18-24	10.0543	2.2661	1.4834	1.6710	9.6683	1.9589	0.4284	1.6317
% Age 25-34	0.0430	2.1833	-0.4437	1.5135	2.5092	1.7743	0.3982	1.4779
% Age 35-44	13.6989	3.8887	0.4930	2.7540	7.5348	3.2285	-0.8323	2.6892
% Age 45-54	3.3703	3.2953	2.5599	1.9841	7.5723	2.3259	1.4421	1.9374
% Age 55-64	7.4039	3.5969	1.7531	2.3792	0.3837	2.7891	1.1989	2.3232
% Age 65+	5.7668	1.6748	-0.6331	1.1178	4.7402	1.3104	-1.0731	1.0915
log(Web)	0.4408	0.3442	0.4402	0.2422	-0.2206	0.2839	0.3778	0.2365
log(DSL)	0.2182	0.0550	-0.2240	0.0407	-0.1534	0.0477	-0.1945	0.0397
log(Cable)	0.1532	0.0548	-0.1327	0.0383	0.0614	0.0449	-0.1194	0.0374
log(Web Media)	-0.3133	0.1414	0.1819	0.0978	-0.0141	0.1146	0.1682	0.0955
log(hourly earnings)	-0.0644	0.1684	-0.0653	0.1197	-0.1759	0.1403	-0.0320	0.1169



log(commute)	-0.0227	0.1844	0.0660	0.1255	0.5699	0.1472	0.0493	0.1226
log(income)	-0.2392	0.2102	0.5195	0.1433	1.5270	0.1680	0.5636	0.1400
log(unemployment rate)	0.0940	0.0672	-0.1363	0.0485	-0.2581	0.0568	-0.1169	0.0473
log(retail wage) % Retail employment	-0.1285	0.2857	0.3138	0.1917	0.8163	0.2248	0.2204	0.1872
	2.5959	1.5145	-4.2466	1.0319	-1.3511	1.2097	-4.4447	1.0076
% Construction	1.0254	0.5587	1.1421	0.4026	-0.3739	0.4719	1.1462	0.3931
% Food Services	-2.6423	2.1455	7.4469	1.4791	2.3690	1.7339	7.2258	1.4442
% Manufacturing	0.0853	0.3150	-0.8337	0.2132	-0.6103	0.2499	-0.7423	0.2082
% Health Care	-2.2025	0.8933	-0.8092	0.6218	0.6549	0.7290	-0.4528	0.6072
log(radio station)	0.3878	0.0552						
log(class A stations)	0.6979	0.2247						
log(class B stations)	1.3370	0.2323						
log(class B1 stations)	0.5012	0.5422						
log(class C stations)	1.4562	0.2729						
log(class C0 stations)	1.7176	0.3658						
log(class C1 stations)	-0.3494	0.2874						
log(class C2 stations)	0.3374	0.3242						
log(class C3 stations)	1.1351	0.3360						
	R <sup>2</sup>	0.9600	R <sup>2</sup>	0.9822	R <sup>2</sup>	0.9912	R <sup>2</sup>	0.9829

Table B.12  
Heteroscedasticity Tests

	Residuals from Log(Albums)		Residuals from Log(Tracks)	
	Coefficient	Standard Error	Coefficient	Standard Error
Test One:				
intercept	0.0539	0.0170	0.0935	0.0211
MSA Coverage	0.0237	0.0212	-0.0104	0.0264
Test Two:				
intercept	0.0693	0.0102	0.0761	0.0127
% in Arbitron	0.0052	0.0177	0.0162	0.0219
Test Three:				
intercept	0.0970	0.0711	0.1539	0.0878
log(population 12+)	-0.0018	0.0050	-0.0049	0.0062
Test Four:				
intercept	0.0744	0.0101	0.0990	0.0072
year = 2005	-0.0047	0.0083	-0.0233	0.0101
year = 2006	-0.0075	0.0082	-0.0228	0.0101

Note: Residuals taken from full sample predictions ( $\hat{m}_3$ )

Table B.13  
Alternative Ways of Allocating Music Exposures from Radio Markets to DMAs

	Log(Albums)		Log(Tracks)		Log(Current)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Assume unobserved have small markets, "assigned DMA"	0.0097	0.0022	0.0112	0.0026	0.0090	0.0021
Based on typical DMA "inside- outside" distribution	0.0104	0.0022	0.0118	0.0026	0.0097	0.0022

Table B.14  
Fixed Effects Models

	Per Capita Albums (weighted)		Per Capita Albums (unweighted)	
	Coefficient	Standard Error	Coefficient	Standard Error
Arbitron ratings	0.0208	0.0021	0.0132	0.0024
year = 2005	-0.0004	0.0001	-0.0005	0.0001
year = 2006	-0.0004	0.0000	-0.0003	0.0000
log(hourly earnings)	-0.0013	0.0010	-0.0010	0.0009
log(income)	0.0129	0.0016	-0.0014	0.0031
log(unemploy rate)	0.0004	0.0002	-0.0001	0.0002
log(retail wage)	0.0022	0.0012	0.0015	0.0013
% Retail employment	0.0008	0.0075	-0.0072	0.0067
% Construction	-0.0005	0.0029	0.0017	0.0017
% Food Services	-0.0060	0.0108	0.0161	0.0097
% Manufacturing	0.0027	0.0039	-0.0059	0.0031
% Health Care	0.0024	0.0027	0.0005	0.0024
	R <sup>2</sup>	0.9535	R <sup>2</sup>	0.9333

Notes: Models absorb a fixed effect for each DMA. Weighted model uses square of DMA population.