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Three Essays on the Organization of Media and Entertainment Industries

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THREE ESSAYS ON THE ORGANIZATION OF MEDIA AND ENTERTAINMENT INDUSTRIES

by

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This final copy of this thesis has been examined by the signatories, and we find that the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

ABSTRACT

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Three Essays on the Organization of Media and Entertainment Industries

Thesis directed by Associate Professor Scott Savage

This dissertation examines the ways in which media and entertainment industries organize and compete, and how this may affect consumer utility. In the first chapter, I consider the use of exclusive contracts among four of the United States' most prominent music festivals in order to examine their influence on local music venues. By utilizing a unique industry and multi-year dataset, as well as variation in the use of exclusive dealing across the country as determined by the location of large music festivals, this paper adds to the paucity of empirical analysis of exclusive dealing and provides new insight into an ignored sector of the music industry. Results show that exclusive contracts correlate with a decrease in the number of venues in affected cities by nine to 35 percent.

In the second chapter, I focus on the operation of these same music festivals. This paper examines what characteristics are important to current commercially successful music festivals when making hiring decisions. A model of customer demand motivates the paper, and the empirical analysis utilizes characteristics important to the negotiation between festival and the band as input in order to determine what is necessary for the festival to attract a sufficient number of consumers.

In the final chapter my co-authors and I examine how consumers value non-price characteristics of local news, providing results unique to the literature. Results show that welfare decreases, but the losses are smaller in large markets. This analysis informs policy questions about the value of local news and how much regulation should be involved.

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Thank you to my adviser, Scott, as well as the rest of my committee for their invaluable help in teaching me how to research. Thank you to my friends, who convinced me that I could do it.

CONTENTS

TABLES

Table

CHAPTER I

Exclusive Dealing and Its Effects: The Impact of Large Music Festivals on Local Music Venues

1.1 Introduction

In June of 2010 Illinois Attorney General Lisa Madigan opened an antitrust investigation of the popular Chicago music festival, Lollapalooza (Knopper, 2010). The basis for this investigation is the exclusivity clause which artists playing the festival must sign, restricting them from playing any public or private concerts within 300 miles of the festival for 180 days prior to and 90 days past the summer event. Among four leading music festivals in the US this is a common requirement, only varying in one of the four festivals (Kot, 2010). This one differing festival is crucial, however, allowing for exploitation of the cross variation between clauses to ensure the interpretation of exclusive dealing as dampening competition. The implicit concern of the Illinois Attorney General and many venues trying to attract musicians is that these massive festivals violate antitrust laws and diminish the ability of local music venues to compete. This paper directly addresses this concern by empirically examining the impact of exclusive dealing on the ability of venues within the radius of these clauses to compete.

The massive annual music festival is relatively new to the US. Despite the success of Woodstock, the model was largely not continued from year to year in the United States as it was in Europe.[1] Without the appropriate management the festivals were not able to achieve commercial viability. Beginning in the early 2000's, however, four of the largest current music festivals in the US were held annually, each achieving profitability. These festivals have very similar three day formats,

[1] For examples see Glastonbury and Isle of Wight Music Festivals in England or Roskilde in Denmark.

attract bands from a variety of music genres, and are the largest in the country. Bands from most contemporary genres are represented; including popular music, rock, independent, folk, rap, hip-hop, punk, and more. Coachella (2001) in Indio, California; Austin City Limits (2002) in Austin, Texas; Bonnaroo (2002) held in Manchester, Tennessee; and Lollapalooza (2005) conducted annually in Chicago have attracted many bands and large audiences while maintaining the exclusive contracts mentioned above (Kot, 2010).[2]

Exclusive dealing is used as a form of vertical integration by firms that cannot legally integrate, or would prefer to have an exclusive relationship without integrating. Exclusivity can be enforced in various ways, but most important for this paper are contractual agreements, specifically music festivals using exclusivity clauses when contracting with musicians. The classical view of exclusive dealing is laid out by the Chicago school (Bork, 1978; Posner, 1981): exclusivity allows the upstream firm in the deal to invest in the downstream firm without fear of free-riding by other upstream firms, creating an environment where the dealer can reduce costs and increase efficiency. Conversely, several authors have addressed the possibility of decreased competition as a result of exclusive dealing. The concern is that firms employing this practice can foreclose competitors or deter entry into a market (Aghion and Bolton, 1987; Bernheim and Whinston, 1998). Such concerns reflect the issue addressed in the antitrust laws and the implicit reason for the Illinois Attorney General's investigation into Lollapalooza.

There is a question of actual enforcement of this clause by the festivals. In 2012, Coachella Music Festival began the unique practice of repeating its performance over consecutive weekends. The exact same lineup of bands played the opening weekend and then performed again the very next weekend so that the festival could sell twice the tickets for the event. In most cases bands would likely look to book additional performances in southern California in between weekends, however, anecdotal evidence by booking agents suggested that performing in the area was limited to "Las Vegas and San Francisco" because of the radius clause.[3] Further anecdotal evidence from interviews with venue operators suggests that some exceptions to exclusive dealing clauses are made, but only for venues owned by companies that operate a festival. These exceptions should do

[2]Lollapalooza began as a travelling festival from 1991 through 1997, but became a stationary three day festival in 2005.

[3]http://www.gpb.org/news/2012/04/24/marooned-in-l-a-for-a-week-coachella-bands-make-do (Accessed 4/24/2012)

nothing to deter the notion that this clause is used as an anticompetitive practice.

Music venues face two possible effects from the presence of these music festivals. The first is that the clause diminishes the ability of smaller firms affected by the contracts to attract enough popular bands to fill their schedule, perhaps leading to shut down or deterring entry. The second, and less obvious possibility is that these festivals create local demand for the bands and various genres of music involved, therefore generating a wider base of artists which can play the regional music venues and stimulating local demand through increasing heterogeneity of preferences. The potential for a demand change means the results of this paper cannot be soley interpreted as an exclusive dealing result, but as the effect of the festival clause and demand considerations. However, given the expectation of a positive effect on demand, any venue effect should be seen as a lower bound impact from exclusive dealing. In the Results section I explore several tests used to assign the effects. In addition to regression discontinuity and falsification tests, I exploit the difference in one festival's clause from all others in order to firmly attribute any competition dampening effect to exclusive dealing.

It is important to consider whether these exclusive deals are common practice for the concert industry. Do music venues also enact such a strenuous clause? From interviews conducted with venue managers this does not seem to be the case. A venue may restrict the band from playing another location in the same city for up to a week, but its difficult to see how this would greatly restrict a band. Bands may perform in a city for multiple nights but the logistics of travel, set-up expenses, and transaction costs would seem to dictate that bands perform in the same location for each concert. These deals do not prevent promotional appearances at local establishments by the band during their stay. In total, the festival clauses are much more restrictive than any venue clause found, and seem to be an atypical agreement in concert production.

Two recent papers expand the condition under which entry can be restricted by exclusive dealing. Segal and Whinston (2000) show that if discriminatory offers are allowed, an upstream firm can reach its exclusion threshold as long as the fee paid to buyers is not greater than their gains from exclusion. If true, the efficiency arguments do not account for a decreasing payment to buyers, and therefore welfare can in fact decrease with the practice. The paper does have the very limiting assumption that contracts cannot ever be breached. According to Simpson and Wickelgren (2007) the lack of breach is a flaw in their argument, and they allow breach and payment of damages in their paper. With the assumption that buyers are Bertrand competitors, refusing the exclusive dealing contract from a seller would only pass on benefits to the final consumer. The conclusion then is that the seller and buyer benefit from the seller monopolizing the upstream through an exclusive contract and that the number of competitors is restricted by the practice, the result looked for in this paper.

Lafontaine and Slade (2008) provide an overview of empirical work on exclusive dealing. They find a paucity of studies and minor effects on competition. The primary problem of empirical studies of the topic revolves around a lack of industries to observe and data difficulties in those that exist. This paper is most similar to several empirical studies, beginning with an analysis of insurance rates, where Marvel (1982) finds that exclusive-dealing contracts are used to protect manufacturer's property rights in non-brand-specific promotional investments. Slade (1998); Sass (2005); Rojas (2011) have addressed exclusive dealing questions within the beer industry, where exclusive dealing is common but may vary geographically or by law. These papers find little evidence of anticompetitive effects within this industry caused by exclusive dealing. In addition, Rojas uses the pass-through rate of exogenous state taxes to assert that the practice can result in higher welfare, primarily from efficiency gains.

This paper takes advantage of the unique geography of music festivals across the US and compares differences in the number of music venues in cities affected by these contracts to those outside of their influence. The areas falling within the radius of these music festival clauses are not obviously different in characteristics from those outside and so the null hypothesis tested is that after controlling for any measurable characteristic that affects the number of music venues there is no difference between cities within a festival radius from outside of that range. Therefore, I create a model using the differences in similar cities to isolate the effect of exclusive dealing. With panel data, regional and time fixed effects allow further control of area or year specific variation.

My contribution to the literature is purely empirical, first providing insight into the sector of the music industry concerned with concert production, a significant revenue generator. While much has been written on the effect of file sharing on record labels and their sales, little work has been done on concerts and their move to profitability. This paper also adds to the dearth of work done on empirical analysis of exclusive dealing, where the industries and structure of markets has not varied much across the few existing papers that have examined the problem. Considering the lack of work in this area, a unique dataset is needed to provide a contribution. For this I've assembled a completely original record of venues across United States cities Due to the incomplete nature of the data, no utility analysis is possible. However, the dataset was created to reflect a homogeneous group of venues, meaning the established decrease in venues associated with exclusive dealing is dampening competition among this narrow sector in the United States. A shift to larger venues is unlikely in this case, as most above the size threshold used for this paper are not music dependent. The competition dampening appears to be a unique result in the literature.

The final contribution of this paper will be to provide some tangible evidence in the investigation of the antitrust policy and potential prosecution in Illinois. The dampening of competition and foreclosure effects hypothesized in the theoretical literature make intuitive sense, but have not been persuasively shown in any practical applications. Claims against Lollapalooza, and transitively the other major festivals in the US are worthy of investigation, and I find that a significant anti-competitive effect does exist. I estimate the impact ranges from a low of about 9 percent decrease in the number of venues against the predicted mean to a high estimate of about 36 percent. Further analysis shows the effect differs depending on the size of the city. These results are robust to alternative models.

The remainder of this paper is organized as follows: Section 2 provides background on concert production and a priori predictions of exclusive dealing effects. In Section 3 I create the models to be estimated. Section 4 introduces the data and provides some initial summary statistics. Section 5 provides results, and Section 6 concludes.

1.2 Background

The music industry is comprised of two primary sources of revenue: recording and distribution of albums by musicians is the most widely studied and well understood sector of these. Specifically, the most extensively researched question in the last 15 years has been the effect of file sharing on record labels and their sales (Liebowitz, 2004; Zenter, 2006; Oberholzer-Gee and Strumpf, 2007), and then the related question of how file sharing affects the frequency and quality of music releases (Waldfogel, 2011).

Concert production has received much less attention: Mortimer et al. (2012) have explored the potential effect of file sharing on concert activities, and in so doing researched how this aspect of the music industry is operated. Connolly and Krueger (2006) review the concert booking process, finding that artists get most of their revenue from touring the country and putting on concerts. Album production typically involves labels taking on the cost of production of an album and paying a very small percentage of its sale price to the artist. Artists usually organize tours through promoters, who finance the events and take 15 to 30 percent of ticket and merchandise revenue in addition to their contractually agreed upon guarantee. For the venue, in addition to a rental fee their primary income comes from concessions and parking. The incentives of the band and promoter are not well aligned with the venue because ticket prices are typically irrelevant to venue profit, and in fact lower prices are likely more beneficial to venues (Mortimer et al., 2012). Fixed costs for a venue consist of lighting and sound systems which can be purchased or rented. In addition, venues must pay one of several representatives of copyright owners a monthly fee, based on venue capacity, as a guarantee against copyright infringement.[4]

The large music festival attracting national artists began in the United States in 1954 with the Newport Jazz Festival (Brant, 2008). The Monterey Pop Festival was a popular production in the late 1960's, and Woodstock, probably the most famous of all rock festivals took place in 1969. However, despite the popularity of these events no festival was a commercial success until the early 2000's. Production of these events involves renting (or on rare occasion, buying) the necessary space, hiring temporary staff and establishing outdoor stages. There are, of course, many smaller music festivals and temporary productions in the US that lack the size and demand of these major events. For scale, Lollapalooza has capped the number of attendees of its event in 2008 and 2009 at 225,000 people. Local and regional festivals cannot come close to matching these numbers. I am not able to obtain contract information for all of these small festivals, so their use of exclusive dealing clauses is unknown. Additionally, there are a considerable number of music festivals in the US, all smaller in size than the four studied that have started and then failed to operate annually. An illustrative example is Vegoose, operated from 2005-2007 by the same promoter as Bonnaroo, this festival was stopped by poor attendence (40,000 tickets sold) and a lack of profitability.[5] I

[4]ASCAP, BMI, and CSAC are the three primary organizations referenced here. Fixed fees are required to account for the possibility that bands "cover" a copyrighted song so that royalties will be collected without the necessity of monitoring each event.

[5]http://www.knoxnews.com/news/2008/may/06/superfly-c-pull-plug-vegoose/ (Accessed 6/1/2011).

justify excluding smaller festivals by arguing that they are less likely to be capable of restricting access to their artists, and even assuming exclusivity clauses that are similarly severe the smaller number of musicians and tickets sold will mean a negligible impact on surrounding venues.

Music festivals must make a substantial investment in order to provide their product. The festival must rent land sufficient to hold many thousands of people, equipment for use throughout the weekend, and hire 100 or more bands of different genres and levels of popularity. This diversity of music and band popularity allows the festival to attract the requisite number of customers to become profitable. The marginal consumer will base the decision to purchase a pass on a simple threshold of utility from the festival lineup. The customer will not be able to see every band in the lineup, so the decision will be based on a few bands which provide the highest utility. The festival uses their exclusive dealing clause to protect the utility of these bands. If venues were allowed to hire the bands for performances on dates around the festival, the consumer could see a longer performance at a local venue for a considerably lower price. This would subtract from the festival utility of the marginal consumer, possibly eliminating her incentive to buy a pass to the festival if a sufficient number of bands from those she wanted to see were playing locally. The exclusive dealing clause allows festivals to invest in their product with the knowledge that the experience of a concert by their performers will be geographically limited for a significant period of time. In terms of exclusive dealing the festival is an upstream firm that intends to prevent free riding by the downstream local venues. As a result of this protection, local venues may not be able to hire the bands that are demanded by their consumers, creating the potential for foreclosure or entry deterrence among venues.

Beyond the exclusive dealing aspect of any festival impact there are also demand considerations for the venues. Economic theory provides the possibility of positive and negative effects. First, consider an area's initital diversity of demand for music. Entry and operation of a music festival could and probably will cause a positive demand shock. These festivals will attract many locals, as seen by their extremely high attendance figures.[6] The locals in attendance are then exposed to new types of music available to them. A resulting widening of music taste in these areas is therefore plausible, leading to a more extensive base of bands and genres of music that can be booked by the local music venues.

[6]Coachella's attendance in excess of 200,000 is generally indicative of attendance in each of these festivals.

Conversely, a potential source of decreasing demand could come from a budget constraint for the amount of music seen in a year. Anecdotal evidence of ticket prices shows the festivals to be considerably more expensive than a typical individual concert by one of its participants. For example, a weekend pass to Coachella in 2011 was \$319.[7] This is in addition to any food, drink, and memorabilila purchases made while attending the festival. Some additional purchases are likely due to the closed nature of these festivals and their length; which extends well beyond the average concert. A survey of ticket prices for Coachella headliners that toured after the festival in 2011: The Arcade Fire, The Strokes, and The Black Keys found average prices before service fees of \$45, \$44, and \$39.[8] While service fees add considerably to ticket prices in most concerts, these are three of the bands that headlined the festival and are therefore considered to be in highest demand and likely priced higher than most other performers. It is clear that these festivals are considerably more expensive than an individual concert, and any consumer attending one would spend a larger than average portion of their music budget on this festival. All of these effects would lead to a reduction in demand for other concerts that are held by local firms.

Disentangling the demand and exclusive dealing effects is difficult. If the demand effect is positive, the results of this paper can be seen as a lower bound of the impact of exclusive dealing. Where demand effects are negative, appropriate association is more perilous. Additional tests in Section 1.5.3 show that the most likely demand effect is positive, making the results showing correlation between decreased venues and exclusive dealing the most feasible explanation.

1.3 Empirical Model Specification

In order to measure the impact of the exclusivity clauses I create several models using city characteristics that are plausibly relevant to the number of venues which locate there. I then ensure robustness through alternative specifications. Each model has number of venues in a city as the dependent variable, and includes an indicator for whether a city is within a festival radius. Identification of the exclusive dealing effect is derived from the difference in the number of venues in cities affected by exclusive dealing from those that are not. Given two identical cities, one inside of a radius and one outside, the effect can be thought of as the decrease in the number of venues

[7] http://consequenceofsound.net/2011/01/coachella-2011-is-about-to-sell-out/ (Accessed 4/23/2011).
[8] Tour dates found on Songkick.com, ticket prices found on venue websites.

the city inside can expect from exclusive dealing.

The baseline model is

$$\begin{aligned} Venues_{it} =&\beta_0 + \beta_1 Festival_{it} + \beta_2 FIT_{it} + \beta_3 PrimaryCity_{it} \\ &+ \beta_4 Metro_{it} + X_{it}\Theta + \alpha_t + \gamma_j + \epsilon_{it} \end{aligned} \tag{1.1}$$

Where all variables are measured by city i in year t. The variable of interest is an indicator which accounts for a city being within a festival radius. This is done in two ways. Equation 1 contains the general festival indicator, where the variable equals one if the city is within a radius of any of the four festivals. In most of the models tested FIT represents the interaction term included. Each festival indicator is interacted with a city's population, the year, or both in order to test how exclusive dealing effects may vary with those measures. X is a matrix of control variables including the log of county income, city and county population, and percentage of the population that is between ages 18 and 44. The vectors α_t and γ_j are year and region fixed effects.[9] $PrimaryCity$ indicates that a festival is located there, acknowledging that there could be something unique about that location that affects the number of venues which also drew the festival to the area. There is also an indicator for a city located in a Metropolotian Statistical Area ($Metro$) without being the major city in that area; anticipating that any cities beside the most populous city in an MSA will likely have less venues, all else equal, because businesses would be inclined to locate in the largest city in the area.

The alternative model is:

$$\begin{aligned} Venues_{it} =&\beta_0 + \beta_1 ACL_{it} + \beta_2 Bonnaroo_{it} + \beta_3 Coach_{it} + \beta_4 Lol_{it} + \beta_5 PrimaryCity_{it} + \\ &\beta_6 Metro_{it} + InterTerms_{it}\Pi + X_{it}\Theta + \alpha_t + \gamma_j + \epsilon_{it} \end{aligned} \tag{1.2}$$

Equation 2 contains individual indicators for each of the four festivals. $Interterms$ is a matrix of interaction terms on the individual festival fixed effects. In addition, a measure of the local radio

[9] City level fixed effects were also tested, but in doing so eliminated considerable useful variation between cities by completely determing 1349 observations across cities that didn't vary across time. When the sample was limited to cities with varied venues, city fixed effects provided results which were largely consistent with the full model. City land area was used as a time invariant variable in an alternative model, providing estimates similar to those presented in the results section.

market is used as a control for music demand in the area in both models. Accounting for radio preferences allows for more city specific control of heterogeneity in music preferences. Music tastes vary from region to region and even city to city, radio measures help to control for the diversity of music tastes. Each of the above specifications are then run with the variable $ConcInd$, which is explained in the Data Section.

Before proceeding it is useful to review the variables of interest and their expected impacts. The central objective of the empirical strategy is to isolate the effects of exclusive dealing on a city's music venues by controlling for demographics and music demand. The null hypothesis is that coefficent estimates on the $Festival$ variable, and alternatively individual variables (ACL, *Bonnaroo*, $Coach$, and Lol) are zero. A negative estimate for these variables shows that all else held constant, cities inside a festival's range have fewer venues than outside. Theory indicates that competition is reduced because of increased costs of entry or decreased variable profits of operating in a market controlled by the exclusive dealing firm. Alternatively, a positive effect would indicate that all else held constant, some demand effect is swamping any exclusive dealing dampening; in this case the demand increase would be due to a change in local preferences.

$PrimaryCity$ should have a positive effect if the cities where festivals locate have unique qualities that allow for a greater number of venues. The $Metro$ variable is anticipated to deliver a negative result. Firms likely make the reasonable assumption that most concert consumers build some travel within a metropolitan area into their costs for music. This fact, coupled with the largest population in the area should cause venues to locate in the most populous city in an MSA over its smaller counterparts, all else constant.

1.4 Data

To answer the research question, data is needed that measures how music venues are distributed across time and between American cities. Songkick.com has collected data on concerts and music tours dating back over 30 years. This company provided me their concert data from 1998 through 2009 in 259 major US cities. Seven of those 259 American cities, all with a population over 100,000, did not provide suitable data for determining venues. Additionally, Anchorage, Alaska and Honolulu, Hawaii are excluded due to possible difficulties attracting touring bands which are unrelated to a music festival. New Orleans is excluded after 2004 because a fundamental change in the city's economy seems likely as a result of Hurricane Katrina. There are 249 cities remaining for the entire sample over the 12 year period. From this data I can determine the number of dedicated venues dependent on touring acts; culling sports venues, theaters devoted primarily to performance arts, and small venues with occasional concerts. The population of music venues is crafted to be a homogeneous group most likely affected by festival clauses. Entry and exit over time, and differences across regions, should allow me to determine and control for general trends in the US market, and then separate those trends from any effects caused by the music festivals.

The dataset was verified by exploring the web presence of each individual music venue, and all firms not devoted to concerts as a product were eliminated. In the case of some music venues which were no longer operational this included looking for reviews on popular sites such as yelp.com, and exploring news stories containing information about the venue in question. There is some concern in the collection of data in the early years of the data set, as the company was not in existence until 2006. Songkick collected data from around the world accumulating over one million past shows before going online.[10] Additionally, past shows can be added by users. As a verification of the accuracy of the website, I performed an audit of the city of Denver. In 2010 every concert listed by the music venues in the paper's dataset was included on the website, Songkick maintained perfect accuracy of the listings in Denver. However, they do not claim to document every concert in the past. Fortunately, not every show need be recorded in order to determine the number of venues in a city, simply enough to determine if a venue is dedicated to music performances in a year. Nevertheless, this paper will use the exclusion of earlier years as a robustness test for each measure. Unfortunately, the incomplete listings of concerts in the earlier years means no comparison of the changing number of concerts in a city, concerts per venue, or other potential utility analyses can be done in this paper.

All models must control for demographics as well as variation in exclusive dealing. As mentioned, city and county level population statistics and county level controls are from the US Census American Community Survey. This project is a series of smaller surveys conducted annually to track community characteristics. Local preferences of music are controlled for in a smaller sample

[10] History found at http://www.songkick.com/info/about (accessed 3/23/2011).

using some various measures of radio listening.[11] All population variables are divided by 100,000.

A complete account of all variables and their sources can be found in the text and are also recorded in Table 2.18 at the end of this paper. The number of venues is the dependent variable in each specification, measured within city i and period t. The venues in the sample have similar characteristics in terms of size and concert bookings. Concert capacity ranges from 400-5,000, with the vast majority of venues falling between 1,000-3,000 in capacity. A venue must demonstrate a commitment to revenue derived from concerts, specifically producing performances similar to those in the festivals. Each venue, therefore, must have performances by artists that have also played at least one of the festivals over their lifespan in order to be considered for the sample.

The $Metro$ variable is an indicator reflecting the fact that the city analyzed is not the primary city in its metropolitan area. The $Percentage18-44$ variable records what fraction of the population of a city is between those ages. Each model is also tested with a radio measure as a control for local concert demand. A variety of measures were tried, but the variable used here is a concentration index. The variable uses eleven broad categories of station format within a city to measure concentration, much like a Herfindahl-Hirschman Index. The variable $ConcInd$ is the sum of squares of the percentages of each of these eleven categories broadcast to a given city. Values of the index range from .08 to .54, with a larger number representing a less diverse radio network within a city. $ConcInd$ should have a negative relationship with the number of venues. A higher value likely indicates a weaker customer base for the music market in general, and concerts more specifically.

1.4.1 Summary Statistics

Table 1.1 provides summary statistics for variables used in the full empirical models, showing cities within a festival radius are quite similar to those without.[12] Because of the length of the sample any city that is counted within a radius was initially outside of the festivals as they did not exist in the late 1990's. One questionable difference between samples is the fact that the county population mean is significantly higher in the summary statistics inside of a clause range. This

[11] Data obtained through confidential communication with the Media Bureau of the Federal Communications Commission.

[12] Table 2.18 in Table 2.18 details the variables used in the summary statistics, and Table 1.17 explains any additional variables used in the Results section.

number is heavily influenced by the Los Angeles area, the Chicago area, and the largest counties in Texas all falling within a festival radius. Additionally, county population is not a major determinant in the number of venues a city operates.

The summary statistics in Table 1.2 describe the cities affected and unaffected before the festivals enter. Of course, any vastly different statistics before the festivals came into existence would call into question the legitimacy of any comparisons in venues between the two. Because 2001 is included, the composition of cities is just slightly different than in Table 1.1 as some cities were within the radius of Coachella and Bonnaroo in that year and are not included in this measure. As the table shows these pre-existing differences did not exist. The average number of venues is slightly larger within, but the difference is not statistically significant. In fact, the only statistically significant difference in relevant variables is in county population which was seen in the entire sample, and explained above.

Table 1.3 notes the changes that occurred after the festivals were established. The venue difference is still not significant, however the cities outside now have the higher average. The demographics remain similar. The average number of entries declined in both areas and exits increased. The average net entry fell by more outside of festival radii, but the difference is not statistically significant. Entry and exit are only truly measured for 3 years in the 1998-2001 sample, as 1998 establishes the baseline for the number of venues in each city. Additionally, the entry and exit numbers are calculated by a venue's appearance or disappearance from the data. If a firm temporarily shut down or simply changed names, the entry and exit statistics cannot account for that. Fortunately, entry and exit measures are only summary statistics, the number of venues is the important statistic for analysis.

Entry continued to exceed exit throughout this period. Any story of exclusive dealing in this paper is not one where growth of music venues was eliminated, growth was instead inhibited by the actions of the much larger music festival. Therefore, any effect is of reduced growth in comparison to what should be expected by cities of the given demographics. This can be seen as exclusive dealing dampening competition, but not eliminating it.

Table 1.1: Summary Statisics Within and Without

Within				Without			
Variable	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**St Dev.**	**Obs**	**T-Test**
Venues	1.658	3.068	777	1.649	2.748	2200	-.272
Population	334,000	530,134	777	302,068	647,708	2200	-1.27
ACL	0.257	0.437	777	0	0	2200	-27.4***
Bonnaroo	0.162	0.369	777	0	0	2200	-20.49***
Coach	0.416	0.493	777	0	0	2200	-39.3***
Lol	0.167	0.373	777	0	0	2200	-20.88***
Northeast	0	0	777	0.12	0.325	2200	10.37***
Midwest	0.19	0.393	777	0.19	0.392	2200	.097
West	0.416	0.493	777	0.359	0.48	2200	-2.9**
South	0.394	0.437	777	0.331	0.269	2200	-13.2***
Income	43,112.27	9237.48	777	43,965.34	9369.07	2200	2.3*
CountyPopulation	2,560,711	3,214,136	777	992,547	1,380,134	2200	-18.37***
Median_age	33.4	2.3	777	34.9	3	2200	11.8***
Entries	0.094	0.366	777	0.123	0.383	1956	1.7*
Exits	0.055	0.265	777	0.084	0.315	1956	2.1*

Notes: T-test - H_0: $\mu_{within} - \mu_{without} = 0$
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.2: Summary Statistics from 1998-2001

Within				Without			
Variable	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**St Dev.**	**Obs**	**T-Test**
Venues	1.42	2.88	289	1.412	2.46	447	.68
Population	316,181	517,576	289	282,302	635,915	447	-1.04
Northeast	0	0	289	0.148	0.355	447	7.12***
Midwest	0.256	0.437	289	0.139	0.346	447	-3.9**
West	0.349	0.478	289	0.389	0.488	447	1.05
South	0.395	0.439	289	0.328	0.197	447	-9.14***
Income	44,578.47	9,437.40	289	44,909.44	9,209.39	447	.6
CountyPopulation	2,155,851	2,944,547	289	783,741	802,656	447	-9.3***
Median_age	32.85	2.1	99	34.643	2.784	150	5.5***
Entries	0.112	0.325	193	0.137	0.382	299	1.4*
Exits	0.047	0.274	193	0.061	0.225	299	-.12

Notes: T-test - H_0: $\mu_{within} - \mu_{without} = 0$
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3: Summary Statistics from 2002-2009

Within				Without			
Variable	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**St Dev.**	**Obs**	**T-Test**
Venues	1.674	3.105	727	1.79	2.805	1265	.68
Population	335,255	529,668	727	305,498	680,078	1265	-1.04
Northeast	0	0	727	0.139	0.346	1265	10.9^{***}
Midwest	0.199	0.4	727	0.187	0.39	1265	-.5
West	0.395	0.489	727	0.361	0.481	1265	-1.7^{*}
South	0.406	0.447	727	0.313	0.191	1265	-16.3^{***}
Income	43,059.63	9,371.91	727	43,558.79	9,292.06	1265	1.1
CountyPopulation	2,485,576	3,167,533	727	829,695	805,513	1265	-17.5^{***}
Median_age	33.522	2.421	727	35.255	3.052	1265	13.1^{***}
Entries	0.091	0.367	727	0.114	0.379	1265	1.2^{*}
Exits	0.056	0.269	727	0.1	0.344	1265	2.8^{**}

Notes: T-test - H_0: $\mu_{within} - \mu_{without} = 0$
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.5 Results

The Results section is divided into the estimates of the maximum likelihood model relating the number of venues in a city to the characteristics most likely to affect them, and then the various robustness checks that ensure their accuracy. There are two estimation methods reported. Considering the number of festivals is nonnegative count data with many zero observations, Poisson estimation is an appropriate candidate. The Poisson does have an equidispersion assumption, so a negative binomial approach is also reported in this paper to allow for variance which differs from the mean. In all of the following tables fixed effects are omitted for space, but year and regional fixed effects are included in each model. The first table referenced in each section provides the marginal effects associated with each of these models in terms of difference from the mean. For ease of interpretation the marginal effects are referenced in the body of the results section. The second table in each section presents the raw results from the three specifications. Because these are maximum likelihood specifications, each coefficient is interpreted as the log difference in count outcomes of the dependent variable from a one unit change in the independent variable, holding all else constant.

1.5.1 Baseline Results

The first results reference the baseline model outlined in Equation 1. Results for this model appear in Table 1.4 and the associated raw effects in Table 1.5. Columns one and two show parameter estimates using the single festival indicator for any city within a festival radius. These results utilize the entire sample. As expected, not being the primary city in a metropolitan area is quite important to how many venues are in a city. $Metro$ estimates are significant and range from a .8 decrease in venues to a 1.2 decrease. One explanation for this substantial effect is opening and movement of venues toward the largest and likely most attractive city in the metropolitan area.

The estimate for city population is significant and certainly more substantial than county population, which is not precisely estimated. Interestingly, inflation adjusted income is never significant as a predictor of venues. Unlike most industries, concert production is not helped greatly by income. The concerts in these venues are not expensive and what the data shows to be more important is the age composition of people in an area. Several age ranges were tested, but predictably the most influential is the percentage of people in the range of 18-44, on the order of .09 additional venues for each additional percentage point. This late youth to maturing adult age range is coveted for its disposable income and desire for entertainment, and the estimates reinforce their importance in the number of venues. The final control variable is the indicator for a city playing host to the festival, the $PrimCity$ indicator. This variable should capture any effect of the unique characteristics specific to a city which attracted one of these major events, but is not precisely estimated and irrelevant in each model, and thus not included in the tables.

Also in this table are results for two different forms of the primary variable of interest. Columns one and two show estimates for the single $Festival$ indicator. The estimates, which are significant, show a .35 to .42 decrease in venues from the mean, holding all else constant. This impact is important given the predicted mean over the entire sample of about 1.6 venues. These estimates are consistent with the idea that the exclusive dealing clauses are effective, and that their purpose is to limit competition in order to drive demand to the festivals. If the results are accurate there is certainly some force decreasing the number of venues here, on the order of an approximately 24 percent decrease compared to the predicted mean.

Columns three and four use an indicator for each individual festival to distinguish effects between festivals. With the exception of the negative binomial estimate of Lollapalooza in column four, all of the estimates are significant. The marginal effects are similar across festivals, with Coachella showing the largest negative effect and Lollapalooza and Bonnaroo the smallest.

The possibility remains that cities are affected differently by exclusive dealing depending on size

Table 1.4: Results excluding Radio - Marginal Effects

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.034***	0.116***	0.028***	0.101***
	(0.00)	(0.03)	(0.00)	(0.03)
CountyPop	0.005*	-0.003	0.011***	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Metro	-1.192***	-0.804***	-1.113***	-0.767***
	(0.08)	(0.09)	(0.07)	(0.09)
Percentage18-44	0.113***	0.089**	0.108***	0.087**
	(0.01)	(0.03)	(0.01)	(0.03)
LogIncome	-0.195*	-0.135	0.093	-0.326
	(0.10)	(0.17)	(0.13)	(0.23)
Festival	-0.373***	-0.408***		
	(0.09)	(0.12)		
FestivalPop	0.074***	0.065*		
	(0.02)	(0.03)		
ACL			-0.564***	-0.573***
			(0.10)	(0.13)
Bonnaroo			-0.445***	-0.386**
			(0.11)	(0.15)
Coach			-0.873***	-0.642***
			(0.07)	(0.11)
Lol			-0.438***	-0.331*
			(0.10)	(0.14)
ACLPop			0.107***	0.107***
			(0.01)	(0.03)
BonPop			0.241***	0.225***
			(0.03)	(0.05)
CoachPop			0.019*	0.001
			(0.01)	(0.03)
LolPop			0.039**	0.022
			(0.01)	(0.03)
Observations	2947	2947	2947	2947
Log Likelihood	-5213.9	-4408.8	-4977.2	-4368.2

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects are included in the model, but excluded from the table for space

Table 1.5: Results excluding Radio Measure

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.0295***	0.108***	0.0262***	0.0974***
	(0.00186)	(0.0274)	(0.00175)	(0.0275)
CountyPop	0.00408*	-0.00315	0.0106***	0.00126
	(0.00178)	(0.00221)	(0.00195)	(0.00251)
Metro	-1.204***	-0.839***	-1.195***	-0.822***
	(0.0831)	(0.0975)	(0.0818)	(0.0977)
Percentage18-44	0.0994***	0.0827**	0.101***	0.0832**
	(0.0101)	(0.0305)	(0.0107)	(0.0302)
LogIncome	-0.170*	-0.126	0.0844	-0.304
	(0.0848)	(0.156)	(0.120)	(0.212)
Festival	-0.354***	-0.418**		
	(0.0916)	(0.140)		
FestivalPop	0.0648***	0.0609		
	(0.0140)	(0.0311)		
ACL			-0.697***	-0.740**
			(0.169)	(0.236)
Bonnaroo			-0.520**	-0.452*
			(0.169)	(0.223)
Coach			-1.240***	-0.827***
			(0.173)	(0.191)
Lol			-0.510***	-0.375
			(0.141)	(0.192)
ACLPop			0.100***	0.102***
			(0.00987)	(0.0307)
BonPop			0.224***	0.216***
			(0.0305)	(0.0500)
CoachPop			0.0176*	0.000980
			(0.00815)	(0.0297)
LolPop			0.0362**	0.0207
			(0.0121)	(0.0313)
Observations	2947	2947	2947	2947
Log Likelihood	-5213.9	-4408.8	-4977.2	-4368.2

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects, as well as Population Interaction terms are included in the model, but excluded from the table for space

or year. Table 1.5 includes an interaction term, $FestivalPop$, relating the $Festival$ indicator to a city's population. The $Festival$ indicator shows a strong negative estimate, but the effect is clearly lessened in larger cities. Specifically, the impact of a festival is about a .4 venue marginal decrease. When the interaction is considered, for every 100,000 person increase in a city's population there is an associated lessening festival impact of .07. It appears that larger cities are better able to avoid the effects of the clauses, and indeed may even experience a net gain in venues.

One explanation for this counterintuitive result relates to the depth of the market in individual cities. If there is a threshhold of music demand and diversity of preferences that must exist within a city to allow for a venue to operate, a festival could help to surpass that threshold. Although the supply of some popular bands may be restricted, the net effect will be exposure to additional genres of music allowing for more venues to cater to diverse preferences. This would be more likely in larger cities, due to the probability that more people would be exposed to the music of the festival and diversify their preferences. Smaller cities would have the same supply constraints on their venues from the festivals' exclusive dealing clauses, but are less likely to be able to reach the threshhold due to their lower populations; making a negative effect on venues more likely.

Using individual festival indicators and interactions, that impression is reinforced at every point. Cities influenced by Austin City Limits and Bonnaroo have the largest mitigating effect from population increases. These results are encouraging to the exclusive dealing interpretation. Coachella and Lollapalooza take place in two of the largest cities in the US. The surrounding metropolitan areas have a consumer base for music that was almost surely well established before their festivals started, and therefore unlikely to benefit from any demand shock of the festival. Because of this industry maturity the effect on the cities does not vary greatly by size in these areas. In contrast, Bonnaroo takes place in rural Tennessee. The surrounding 300 mile radius falls largely within southern states. While the southern fixed effect is excluded from the table, it is negative and significant when compared to all other regions. The 300-mile radius is known more for its country and bluegrass history than a variety of "jazz, Americana, hip-hop, electronica, and just about any contemporary music you can think of."[13] By attracting visitors from the surrounding area the festival could be expanding local exposure to this music, and therefore increasing the base

[13] Quoted from description at http://Bonnaroo.com (accessed 3/24/2011).

of bands venues can book.[14]

1.5.2 Controlling for Music Demand with Radio

The results in Table 1.6 include a measure for radio in the years 2002-2005, 2007, and 2009. Radio in this instance is a simple proxy for music taste varying by metropolitan area. A number of papers have noted the positive relationship between the diversity of radio formats and total listeners in the market. Rogers and Woodbury (1996) use 1987 data and find a positive relationship of just under 20 percent between an increase in the number of stations and the corresponding change in number of formats. Further, they find that an increase of formats is associated with about a 22.5 percent increase in listeners. Using a more extensive 243 market dataset from 1993 to 1997, Berry and Waldfogel (1999b) test the same premise with regards to firm organization. The authors find a weakly positive relationship between increased formats and increased listeners. They note that although their evidence is weaker than the cross sectional evidence of Rogers and Woodbury (1996) and Berry and Waldfogel (1999a), their panel data may suffer from measurement error in formats.

Following their premise, this paper then makes a common assumption to justify decreases in concentration as a proxy for diverse music demand, namely that if the demand exists in a city to make a format profitable then additional firms using that format will enter the market. Additionally, if the market will support a radio format then music venues can expect concert demand in that same genre. The more concentrated the radio market the less diverse the demand for music. A homogenous population limits the genres consumers demand and means a smaller group of artists that each venue can book. With this specific control of taste on such a small scale, the impact of exclusive dealing is further isolated. The radio data only covers six of the twelve years, but the similarity of the estimates to the original model proves this sufficient to interpret the model and the associated effect of festivals as being properly specified.

The control variables are not overtly affected by the addition of this index, showing generally the same significance and magnitude as existed when they were excluded. Turning again to the general festival indicator in columns one and two, the effect is to strengthen slightly the negative impact from being located in a festival radius. In results not reported here, adding the radio measure

[14] Additionally, a model including year-festival interactions to test the varied impact of a festival clause by year was tested. No table is included because under this model there is a notable lack of significance in the year-festival interaction estimates, so any of the trends mentioned are not definitively different from zero.

strengthens already large positive regional effects (compared to the South) for the Midwest and Northeast, and further decreases the already weak estimate of the West indicator. So accounting for taste in music on the city level certainly does not diminish the effect of exclusive dealing, and in fact demand is likely more accurately measured than is possible using fixed effects alone.

Estimates of the parameters on individual festivals are all strengthened very slightly. Looking at Austin City Limits, Coachella, and Lollapalooza all estimates are now negative, significant, and with a slightly greater impact. Conversely, the interaction terms, not reported here for space lose most of their effect. Although still significant, the results are so small as to remove any serious effect from population increases. This loss of importance strenghtens the idea that larger cities support more venues not only through their population, but diversity of music preferences. Overall, including this measure for music taste and diversity seems to encourage the possibility of anticompetitive effects from the festival clauses.

1.5.3 Robustness Results

The first robustness tests answer two questions, whether the radius clause is at work here or if there is simply some other factor related to the festival or area driving the difference. The initial step is to see if there are demand shocks in the region coming from the festivals. Additionally, I will investigate whether or not there is some fundamental difference between cities in and outside before these festivals started.

The question of a demand effect makes interpretation of the results on exclusive dealing more difficult. In general, if a festival has a net positive or no demand effect then the results can be seen as entirely attributable to exclusive dealing. Fortunately for this study Coachella's exclusive dealing clause differs from the others, in that instead of a 300 mile radius around the festival, the clause names many specific Southern California counties that a band cannot play in (Kot, 2010). This creates an effective radius of approximately 200 miles around Indio, California. In the first two columns of Table 1.9, with raw results in Table 1.8, I test the impact on venues that comes with a city being in this distance which would fall under exclusive dealing in any of the other festivals, but does not with Coachella's clause. The variable *CoachExclusion* measures the effect of being immediately outside of the festival's radius. Clearly, the impact is substantial, and would seem to indicate that the demand effect is causing a positive influence on number of venues in the absence

Table 1.6: Results with Radio - Marginal Effects

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.030***	0.066*	0.022***	0.051*
	(0.00)	(0.03)	(0.00)	(0.02)
CountyPop	0.005	0.000	0.019***	0.008*
	(0.00)	(0.00)	(0.00)	(0.00)
Metro	-1.167***	-0.821***	-1.063***	-0.768***
	(0.10)	(0.11)	(0.08)	(0.10)
Percentage18-44	0.122***	0.131***	0.118***	0.123***
	(0.01)	(0.01)	(0.01)	(0.01)
LogIncome	0.090	-0.327	-0.264	-0.411*
	(0.23)	(0.22)	(0.20)	(0.20)
Festival	-0.459***	-0.633***		
	(0.10)	(0.14)		
FestivalPop	0.072***	0.102**		
	(0.02)	(0.03)		
ConcInd	-0.097***	-0.055***	-0.077***	-0.048***
	(0.01)	(0.01)	(0.01)	(0.01)
ACL			-0.497***	-0.737***
			(0.13)	(0.12)
Bon			-0.581***	-0.552***
			(0.11)	(0.14)
Coach			-1.052***	-0.848***
			(0.11)	(0.12)
Lol			-0.395***	-0.463***
			(0.12)	(0.11)
ACLPop			0.000***	0.000***
			(0.00)	(0.00)
BonPop			0.000***	0.000***
			(0.00)	(0.00)
CoachPop			0.000***	0.000
			(0.00)	(0.00)
LolPop			0.000***	0.000*
			(0.00)	(0.00)
Observations	1468	1468	1468	1468
Log Likelihood	-2555.4	-2222.7	-2441.6	-2200.9

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects are included in the model, but excluded from the table for space

Table 1.7: Results including Radio Measure

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.0270***	0.0598*	0.0219***	0.0481**
	(0.00205)	(0.0249)	(0.00213)	(0.0178)
CountyPop	0.0045	0.0002	0.018***	0.0073*
	(0.0028)	(0.0023)	(0.0036)	(0.0034)
Metro	-1.218***	-0.854***	-1.203***	-0.833***
	(0.117)	(0.126)	(0.111)	(0.122)
Percentage18-44	0.112***	0.125***	0.117***	0.121***
	(0.00805)	(0.00948)	(0.00772)	(0.00841)
LogIncome	0.0818	-0.304	-0.260	-0.400*
	(0.209)	(0.204)	(0.202)	(0.197)
Festival	-0.422***	-0.613***		
	(0.101)	(0.146)		
FestivalPop	0.0638***	0.0939**		
	(0.0142)	(0.0290)		
ConcInd	-0.0887***	-0.0520***	-0.0761***	-0.0471***
	(0.0104)	(0.0101)	(0.00974)	(0.00954)
ACL			-0.615**	-1.040***
			(0.210)	(0.244)
Bon			-0.798***	-0.751**
			(0.219)	(0.257)
Coach			-1.689***	-1.195***
			(0.320)	(0.243)
Lol			-0.418*	-0.480**
			(0.174)	(0.172)
ACLPop			8.81e-06***	1.29e-06***
			(1.21e-07)	(2.46e-07)
BonPop			2.50e-06***	2.73e-06***
			(3.76e-07)	(4.86e-07)
CoachPop			2.35e-07***	3.3e-07
			(4.88e-08)	(2.19e-08)
LolPop			3.61e-07***	5.62e-07*
			(8.61e-08)	(2.34e-08)
Observations	1468	1468	1468	1468
Log Likelihood	-2555.4	-2222.7	-2441.6	-2200.9

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects, as well as Population Interaction terms are included in the model, but excluded from the table for space

of the clause.[15] The final two columns estimate a similar model, but compare the effect of being from 201-300 miles away from the other festivals with all other cities within those radii. These cities, covered by a clause unlike Coachella, show no significant difference from those within 200 miles of a festival. If demand effects were the primary cause of the venue dampening this difference across festivals should not exist. The fact that it does encourages interpretation of an exclusive dealing effect

Table 1.8: Coachella ED Test

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.0885***	0.0885***	0.104***	0.179***
	(0.00806)	(0.00806)	(0.00871)	(0.0213)
CountyPop	-0.00659	-0.00660	-0.00715	-0.00404
	(0.00545)	(0.00545)	(0.00445)	(0.00302)
Metro	-0.852***	-0.852***	-0.883***	-0.276
	(0.217)	(0.217)	(0.150)	(0.177)
Percentage18-44	0.409	0.409	0.0596*	0.0437
	(0.241)	(0.241)	(0.0263)	(0.0235)
LogIncome	4.887***	4.887***	1.474***	1.121**
	(0.552)	(0.552)	(0.297)	(0.381)
CoachExclusion	1.427***	1.427***		
	(0.140)	(0.140)		
201 to 300			-0.0116	0.0686
			(0.106)	(0.115)
	(10.68)	(10.68)	(3.067)	(3.830)
Observations	514	514	1053	1053
Log Likelihood	-485.6	-485.6	-1571.6	-1386.1

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects are included in the model, but excluded from the table for space

Table 1.10 addresses other possibilities. The first three columns include a variable designed to test the mileage impact. Any city between 301-400 miles of a festival was not included in the original Festival variable, but is now counted with the $FourHundredFestival$ variable to see if there is a similar effect on these cities just outside of any clause. If the only impact is a demand shock to a region then the estimates should be similar to the baseline. If, however, the festival clause is responsible then the estimates should be near zero. In columns one and two the $FourHundredFestival$

[15] The same test was performed for $CoachExclusion$ against all of the other festivals in the study. The result was not as substantial, but still quite large and significant.

Table 1.9: Coachella ED Test - Marginal Effects

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.036***	0.036***	0.083***	0.137***
	(0.01)	(0.01)	(0.01)	(0.02)
CountyPop	-0.003	-0.003	-0.006	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)
Metro	-0.399***	-0.399***	-0.667***	-0.206
	(0.10)	(0.10)	(0.11)	(0.13)
Percentage18-44	0.165*	0.165*	0.048*	0.033
	(0.08)	(0.08)	(0.02)	(0.02)
LogIncome	1.979***	1.978***	1.182***	0.858**
	(0.35)	(0.35)	(0.25)	(0.29)
CoachExclusion	0.999***	0.999***		
	(0.20)	(0.20)		
201 to 300			-0.009	0.054
			(0.08)	(0.09)
Observations	514	514	1053	1053
Log Likelihood	-485.6	-485.6	-1571.6	-1386.1

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects are included in the model, but excluded from the table for space

indicator is not significant or important. The estimates are -.04 and .08. So while these cities could still potentially have some extremely small demand effects there is no indication that they are negatively impacted by the clause as those cities within 300 miles appear to be. These results help to identify the original estimates of the impact as specifically caused by the clauses.

Table 1.10: Festival Robustness Test - Marginal Effects

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.035***	0.144***	0.035***	0.149***
	(0.00)	(0.02)	(0.01)	(0.04)
CountyPop	0.008***	-0.005*	0.006	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)
Metro	-1.349***	-0.797***	-1.232***	-0.736***
	(0.08)	(0.09)	(0.17)	(0.16)
Percentage18-44	0.107***	0.085**	0.050	0.020
	(0.01)	(0.03)	(0.05)	(0.02)
LogIncome	0.013	-0.070	0.495	0.521
	(0.19)	(0.24)	(0.59)	(0.38)
FourHundredFest	-0.041	0.079		
	(0.10)	(0.10)		
EverFest			0.077	-0.084
			(0.15)	(0.13)
Observations	2947	2947	729	729
Log Likelihood	-5299.9	-4418.7	-1264.3	-1021.1

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects are included in the model, but excluded from the table for space

The second issue is a possible fundamental distinction in cities inside and out, beginning before the festivals. Are the cities simply different or did these festivals change the climate for music? The $EverFest$ variable in columns three and four of Table 1.10 is an indicator only used in the years 1998-2001, equal to one if the city will be within a radius in the future. This sample is smaller than the original as it only includes cities outside of the festivals' impact through 2001, and any city in this time period which will soon have to contend with exclusive dealing. All cities in the Coachella or Bonnaroo ranges will only be in the sample through 2000 as those festivals started in 2001. The variable estimates the effect of being in a festival radius before the festivals began, so a significant result here would call into question any impact on venues. Again, neither of these estimates are significant and the sign switches between specifications, reaching a marginal value of .077 with the

Table 1.11: Festival Robustness Tests

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.0304***	0.134***	0.0339***	0.158***
	(0.00201)	(0.0189)	(0.00451)	(0.0476)
CountyPop	0.00704***	-0.00509*	0.00615	-0.00364
	(0.00152)	(0.00205)	(0.00333)	(0.00454)
Metro	-1.361***	-0.825***	-1.409***	-0.872***
	(0.0838)	(0.0968)	(0.174)	(0.195)
Percentage18-44	0.0931***	0.0784**	0.0487	0.0215
	(0.00993)	(0.0291)	(0.0520)	(0.0215)
LogIncome	0.0144	-0.0403	0.486	0.552
	(0.164)	(0.225)	(0.567)	(0.400)
FourHundredFest	-0.00106	0.0705		
	(0.0821)	(0.0798)		
EverAny			0.0748	-0.0900
			(0.146)	(0.137)
Observations	2947	2947	729	729
Log Likelihood	-5299.9	-4418.7	-1264.3	-1021.1

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects are included in the model, but excluded from the table for space

negative binomial and a -.084 with Poisson. This test shows it is impossible to attribute any of the difference in the venues to being in a radius before the festivals began, holding all else constant. The cities in a festival radius were not fundamentally different beforehand.

There is some concern about collection of the early years of the dataset. To ensure results are not being driven by noise in the first years of the sample, Table 1.12 drops any observations before 2001. Of course, this does not allow for any trending in venues before the festivals began, but does allow for a comparison of the estimates with the complete set. As is clear and encouraging the control variables have not been greatly impacted by dropping 1998-2000. Still significant are population, $Metro$, and percentage of young adult population. In addition, the magnitudes are similar to the original model, proving dropping the early data does not greatly move the results and justifying the collection of the first three years of the data. Further, a small movement in any control variable is warranted, given that the pre-festival trends can no longer be accounted for in this model.

The variables of interest are also largely unaffected. The estimate on the $Festival$ variable has a slightly more substantial impact than in the original interaction of the baseline, reaching a marginal decrease of almost .57 venues. Considering the individual festival indicators in columns three and four the effects only strengthen. Each festival shows an identical trend to that in the baseline. The only plausible explanation remaining that could affect our results is the possibility that there is some longer trend beginning before 1998 not being picked up in the sample. It is clear, however, that the results on exclusive dealing are not being driven by any errors in the early years. All estimates are still consistent with the early analysis. Finally, in results not included here, I exclude 2008-2009 from the model to test the possibility that the global recession drove some of the results. Estimates in that model were consistent with all others, showing any effect from the recession was similarly felt by all firms regradless of festival clauses.

Table 1.14 tests models that help determine a separation of demand and exclusive dealing effects, with raw results in Table 1.15. The first two columns include a variable for the area in the Ohio Valley that had overlapping exclusive dealing effects from 2005 through 2009 with Bonnaroo and Lollapalooza. This overlap variable shows an increase in venues over other cities affected by the two festivals of about .15, or about five percent given a mean of three venues in this area and time period. This area was affected by the Bonnaroo clause since its inception in 2001, and added

Table 1.12: Post 2000 Robustness Test - Marginal Effects

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.034***	0.084***	0.024***	0.064***
	(0.00)	(0.01)	(0.00)	(0.01)
CountyPop	0.002	-0.003	0.019***	0.006*
	(0.00)	(0.00)	(0.00)	(0.00)
Metro	-1.144***	-0.795***	-1.058***	-0.745***
	(0.05)	(0.08)	(0.05)	(0.07)
Percentage18-44	0.129***	0.141***	0.121***	0.132***
	(0.00)	(0.01)	(0.00)	(0.01)
LogIncome	-0.314**	-0.474*	-0.561***	-0.541**
	(0.11)	(0.19)	(0.11)	(0.17)
Festival	-0.430***	-0.568***		
	(0.05)	(0.09)		
FestivalPop	0.085***	0.100***		
	(0.01)	(0.02)		
ACL			-0.525***	-0.649***
			(0.09)	(0.12)
Bonnaroo			-0.502***	-0.511***
			(0.08)	(0.14)
Coach			-1.130***	-0.843***
			(0.05)	(0.08)
Lol			-0.393***	-0.468***
			(0.07)	(0.10)
ACLPop			0.100***	0.132***
			(0.01)	(0.02)
BonPop			0.259***	0.287***
			(0.02)	(0.05)
CoachPop			0.016*	0.036*
			(0.01)	(0.02)
LolPop			0.029**	0.057*
			(0.01)	(0.02)
Observations	2218	2218	2218	2218
Log Likelihood	-4011	-3360.3	-3796.3	-3325.8

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects are included in the model, but excluded from the table for space

Table 1.13: Post 2000 Robustness Tests

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.0288***	0.0774**	0.0231***	0.0614**
	(0.00183)	(0.0280)	(0.00193)	(0.0228)
CountyPop	0.00153	-0.00233	0.0180***	0.00536
	(0.00250)	(0.00245)	(0.00344)	(0.00292)
Metro	-1.109***	-0.812***	-1.143***	-0.793***
	(0.0952)	(0.103)	(0.0920)	(0.0996)
Percentage18-44	0.109***	0.129***	0.113***	0.126***
	(0.00620)	(0.00834)	(0.00610)	(0.00757)
LogIncome	-0.262	-0.428*	-0.523**	-0.514**
	(0.176)	(0.168)	(0.176)	(0.164)
Festival	-0.383***	-0.558***		
	(0.0920)	(0.142)		
FestivalPop	0.0721***	0.0913**		
	(0.0139)	(0.0308)		
ACL			-0.629***	-0.855***
			(0.173)	(0.220)
Bonnaroo			-0.610***	-0.638**
			(0.172)	(0.225)
Coach			-1.744***	-1.149***
			(0.292)	(0.216)
Lol			-0.446**	-0.568***
			(0.148)	(0.157)
ACLPop			0.0944***	0.127***
			(0.0103)	(0.0260)
BonPop			0.243***	0.275***
			(0.0306)	(0.0452)
CoachPop			0.0146	0.0344
			(0.00872)	(0.0255)
LolPop			0.0276	0.0543*
			(0.0143)	(0.0245)
Observations	2218	2218	2218	2218
Log Likelihood	-4011	-3360.3	-3796.3	-3325.8

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects are included in the model, but excluded from the table for space

Lollapalooza's clause in 2005. The addition should not have had a substantial exclusive dealing effect, given that many bands overlapped between the festivals and the fact that these festivals never took place more than 60 days apart, making substantial additional loss from the second clause unlikely. This overlap effect is therefore most likely from a demand increase.

Table 1.14: Two Hundred to Three Hundred Miles - Marginal Effects

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
[1em] Population	0.139***	0.150***	0.142***	0.174***
	(0.03)	(0.03)	(0.02)	(0.03)
CountyPopulation	0.091***	0.108***	0.033**	0.023*
	(0.01)	(0.02)	(0.01)	(0.01)
Metro	-1.724***	-1.581***	-0.139	-0.102
	(0.41)	(0.42)	(0.20)	(0.17)
Percentage18-44	0.090***	0.090***	0.091***	0.105***
	(0.01)	(0.01)	(0.02)	(0.02)
LogIncome	0.188	-0.011	0.842	0.657
	(0.39)	(0.60)	(0.46)	(0.40)
Overlap	0.156	0.146		
	(0.17)	(0.18)		
201 to 300			-0.052	-0.106
			(0.13)	(0.12)
Observations	241	241	453	453

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The third and fourth columns of Table 1.14 contain the variable for any city within 201-300 miles of the festival city. This specification is run only against those cities immediately outside of the clause border, at 301-400 miles away. At this distance any demand effect should be dampened, and the expectation would be of a decrease in venues from exclusive dealing. The sample is much smaller leading to lower significance, but the coefficients on the 201 to 300 variable are negative and given the mean number of venues in this sample of 1.48, represent a decrease in venues from four to seven percent. If this area is seen as one affected only by the exclusive dealing clause then the exclusive dealing effects are somewhere between 11 and 77 percent of the broad effects found earlier. These numbers are smaller than the estimates from the entire sample, however, at one-seventh the observations the model also lacks much of the explanatory power of the larger sample. The negative effect on venues is consistent across all models tested, and most importantly shows

Table 1.15: Two Hundred to Three Hundred Mile Test

	Poisson Venues	Neg Bi Venues	Poisson Venues	Neg Bi Venues
Population	0.139^{***}	0.150^{***}	0.148^{***}	0.178^{***}
	(0.0285)	(0.0299)	(0.0218)	(0.0254)
CountyPop	0.0909^{***}	0.108^{***}	0.0293^{*}	0.0211^{*}
	(0.0125)	(0.0181)	(0.0115)	(0.0104)
Metro	-1.724^{***}	-1.581^{***}	-0.0819	-0.0675
	(0.414)	(0.417)	(0.193)	(0.163)
Percentage18-44	0.0927^{***}	0.0951^{***}	0.121^{***}	0.145^{***}
	(0.00761)	(0.00878)	(0.0183)	(0.0220)
LogIncome	4.887^{***}	4.887^{***}	1.474^{***}	1.121^{**}
	(0.552)	(0.552)	(0.297)	(0.381)
Overlap	0.156	0.146		
	(0.165)	(0.178)		
201 to 300			-0.00294	-0.0516^{*}
			(0.019)	(0.021)
Observations	241	241	453	453
Log Likelihood	-419.4	-418.3	-645.7	-636.1

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time and Region Fixed Effects are included in the model, but excluded from the table for space

that in the absence of demand effects the exlcusive dealing clause is the most likely cause of a venue decrease.

1.5.4 Exclusive Dealing Example

This paper has reported various specifications and estimates measuring the exclusive dealing impact on local firms. In order to illustrate the effect on a specific city I will create an example. Using the general Festival indicator found in columns one and two of all tables with a population interaction term, and evaluating at the mean value of all indepedent variables, the predicted number of venues is 1.634. The marginal effect of the exclusive dealing clause in the base model is between -.37 and -.41. All else equal, the average city inside of a festival radius has a predicted value of about 1.234 venues, or approximately a 25 percent decrease when compared to a city outside. As population increases this effect diminishes. For every 100,000 person increase above the mean population, the effect is lessened by about .07. Of course, the population coefficient is also significant and positive, at about .075 venue increase per 100,000. These two effects working together, holding all other variables at their mean value, show that a 275,000 person increase beyond the average would elminate the predicted effect of the festival. This implies that smaller cities are disporportionately affected by the exclusive dealing, and in fact at some level of population the total number of venues in a city may benefit from a festival's presence. Again, this result can be explained if larger cities have more diverse music preferences, swamping the supply constraints from exclusive dealing. In this scenario, smaller cities are more strongly influenced by the constraint on supply and do not benefit from heterogeneous preferences.

1.6 Conclusion

The exclusive dealing that the four major American music festivals engage in has some negative effect on the local music venues in the affected cities; either through foreclosure, dampening competition, or increased barriers to entry. By attracting artists to their events with larger payouts and bigger crowds the festival locks the artist into a short-term exclusive deal preventing further concerts in the area. The benefits to the festival are clear, forcing local residents to buy passes to the event if they want to enjoy their favorite band in the near future drives up demand and protects their investment. Because of the typically brief nature of a concert tour venues will likely have trouble booking those acts again in the same year.

Estimates from the models show that the number of venues in affected areas falls by between .15 and .6 venues when compared with comparable cities outside of their range, or a 9 to 36 percent decrease against the predicted mean. The effects are more strongly felt in less populated cities, with larger cities avoiding the brunt of the clause. Looking at each festival individually helps to distinguish the effects. The greatest festival impact comes from Coachella, where the decrease is approximately .7 to .9 venues per city within the range and the cities around Coachella do not seem to have the same diminishing effect with population. With various robustness checks it is apparent that this effect comes primarily from exclusive dealing and not from fundamental differences in the area or demand shocks resulting from the events. However, this is not uniformly true. The Bonnaroo festival shows a negative impact for smaller cities, but the total effect of the festival in this area seems to be an increased number of venues. I put forward the idea that prior to the festival's entry larger cities which fall under the exclusive dealing of Bonnaroo exhibited more homogenous preferences and a developing concert industry. Therefore, the festival has an increased positive effect on demand in these cities and causes a surge in venues in this area when compared to their counterparts.

The models in this paper do not distinguish between foreclosure and entry deterrence as the primary cause of the negative effect of exclusive dealing. Anecdotal evidence, however, points toward deterrence as the most likely cause. As can be seen in the summary statistics, the mean number of venues increases in both areas throughout this period. This is to be expected as the number and importance of concerts in the music industry is increasing. The effect from exclusive dealing comes from mean venues increasing less in those regions affected by a festival than those outside. Entry deterrence fits this evidence better, where exclusive dealing clauses are slowing growth through preventing potential entrants versus driving out existing firms.

Further work on this topic could evaluate the decision making of festivals. Specifically, do the festivals use their competitive advantage to promote quality artists and expand demand or simply present established acts that would perform in local venues without the festival, thereby reducing competition without broadening preferences. This paper is limited to establishing an anticompetitive effect for a homogenous group of music venues, those most likely to be affected by the festival clause. An extensive dataset extending beyond what is currently avaiable may allow for a more thorough utility analysis which could test the overall efficiency of these practices. Additionally, closer analysis of the necessity of the length and severity of the specific clauses in protecting investment would be needed.

Table 1.16: Variable List from Summary Statistics

Variable	Description and Data Source
Venues	The number of venues in a city. Source: Derived from Songkick.com
Population	Population of the city. In results, value is divided by 100,000. Source: US Census, American Community Survey
ACL	Indicator variable for a city within 300 miles of Austin, TX. In summary statistics represents percentage of sample in this range.
Bonnaroo	Indicator variable for a city within 300 miles of Manchester, TN. In summary statistics represents percentage of sample in this range.
Coach	Indicator variable for a city within Coachella's ED range. Specified counties in southern California. In summary statistics represents sample in range.
Lol	Indicator variable for a city within 300 miles of Chicago, IL. In summary statistics represents percentage sample in this range.
Directional Indicators	Indicators determined by region
Income	Median Household Income in county containing a given city. CPI adjusted . (2000 base year) Source: US Census, ACS
CountyPop	Population of the county containing a given city. In results, value is divided by 100,000. Source: US Census, ACS
Median_age	Median age in county containing a given city. Source: US Census, ACS
Entries	Number of venue entries in the city in a year. Source: Songkick.com
Exits	Number of venue exits in the city in a year. Source: Songkick.com

Table 1.17: Additional Variable List from Results

Variable	Description and Data Source
Metro	Indicator assigned to non-primary cities in an Metropolitan Statistical Area
LogIncome	Log of the median income in county containing a given city. Source: US Census, ACS
Percentage18-44	Percentage of population in county containing a given city aged 18-44. Recorded in whole numbers Source: US Census, ACS
Festival	Primary variable of interest. General indicator for a city within a festival radius.
ConcInd	Concentration Index of Radio described in text. Much like an HHI. Source: FCC, obtained by confidential communication with the Media Bureau
PrimCity	Indicator for the city a festival is held in. Limited to Austin, Chicago, and Los Angeles.
FourHundredFestival	Indicator for any city between 301-400 miles of a festival or 250 miles from Coachella.
EverFest	Indicator for a city within a festival range in the years before the festival started.
EverAny	Indicator for a city that will fall under a festival radius in the future, but hasn't yet.
FestivalPop	An interaction of the festival indicator and City Population.
ACLPop	An interaction of the ACL indicator and City Population.
BonPop	An interaction of the Bonnaroo indicator and City Population.
CoachPop	An interaction of the Coachella indicator and City Population.
LolPop	An interaction of the Lollapalooza indicator and City Population.
CoachExclusion	Indicator for any city that falls outside of Coachella's clause, but would be in the radius of the other festivals in this sample.
201 to 300	Indicator for a festival affected by a radius clause that is within 201 - 300 miles.
Overlap	Indicator for any city that falls in both the Bonaroo and Lolapalooza radii.

CHAPTER II

The Importance of Quality: How Music Festivals Achieved Commercial Success

2.1 Introduction

The United States has a rich history of major music festivals providing memorable performances to satisfied audiences. Productions such as the Newport Jazz Festival, the Monterrey Pop Festival, and Woodstock were early successes in terms of attracting huge audiences. Additionally, they are some of the most influential events in music history. They were not, however, commercial successes, and despite their popularity none became annual events. In fact there were no festivals held annually in the same location on the scale of several current American festials until the 21st century.[1] Why was there such a failure for a production that currently exists in commercially successful forms? This paper explains the delay in production of the annual music festival in terms of a need to optimize the mixture of the inputs of the festival, the bands, between established commercial successes and those bands of high quality without notoriety.

Quality differentiation is usually discussed in terms of the difference in cost paid by the firm and the vertically differentiated utility consumers derive from the levels of quality. Music festivals must contend with some degree of vertical differentiation within each type of music, as well as horizontal differentiation between genres. Large music festivals can inhibit the ability of individual music venues to operate through the use of exclusive deals with the artists they hire,[2] but there is

[1] The largest festivals in the US are Austin City Limits, Bonnaroo, Coachella, and Lollapalooza; all studied in this paper.

[2] American festivals such as Austin City Limits, Bonnaroo, Coachella, and Lollapalooza all require restrictive exclusive deals.

also the possibility that the festival can cause an increase in demand for live music in that same area. Production of these events involves hundreds of bands, and they are attended by hundreds of thousands of people. These festivals are exposing consumers to a broad range of music products, and generating some demand for bands and genres of music that would not exist without the exposure. Festivals must choose how to generate their product with the dual questions of what demand for tickets the marginal band will provide weighed against the budget constraint of hiring that band in the context of their quality level.

A substantial literature is devoted to determining firm quality decisions and how they affect consumer choices. The early works of Lancaster (1971) and McFadden (1977) began the research into the importance of product characteristics. Wolinsky (1983) investigates the possibility that product quality can be used as a signal to consumers. Further empirical work has been done by Berry et al. (1995), Petrin (2002), and others that has explored empirical methods for estimating models of consumers with heterogeneous preferences and the impact of varied product characteristics. Mazzeo (2002a), Chu (2010), and Matsa (2011a) all explore the relationship between the level of competition and product quality.

Music festivals face a market in which they have little direct competition, but must convince consumers of the value of their product. Despite the extensive literature, little work has been done considering quality and characteristic decisions where the firm must negotiate with their inputs. This paper examines the music festival industry in order to consider the level of quality and other product characteristics that a firm finds important in production of its final good, and considers the possibility that the cost of an input may not be perfectly correlated with its quality if consumers are not aware of the quality level of all of the inputs before buying a ticket. In doing so I determine what characteristics of a band are important for festivals when choosing the final product they will provide, with an emphasis on the effect of recent quality on hiring.

The ultimate objective of the festival is profit maximization.[3] The producers of these events create a "lineup," or compilation of musical acts that constitute a festival. Within the lineup there is a hierarchy of bands. The "headliners," or most highly demanded bands will receive the most prominent placement in promotional material and are expected to draw the most customers. Not

[3]There are of course possible alternative objectives of some other music festivals, such as maximizing utility of consumers without generating a negative profit. However, given the nature of these festivals and the corporations that own them, profit maximization is not an unreasonable assumption.

surprisingly, they are also paid the highest fee. Below the headliners are bands of lower expected demand that cannot command as large a payment as the headliners. Within this hierarchy there is considerable variation in genre of music, experience, and perceived quality. I determine what is important to festivals, if festivals are early promoters of quality bands, and if a band must sustain their quality in order to become a headliner in a festival.

Quality here only refers to highly regarded contemporary contributions to the music industry. It is possible, for instance, for an artist to continue to profit off of a product of quality decades after its debut and without any additional works of significance in the interim. Quality measures in music must be somewhat subjective. Consumer preferences for music genres and bands are horizontally differentiated, with few absolutes in quality ranking. Favorite genres, songs, bands, and styles vary among age groups, ethnicities, and nationalities. Even within a homogenous group there are differing opinions on quality. The expression, "there is no accounting for taste" seems perfectly crafted to describe varied opinions about music. Any measure of overall quality of music in a year must capture some of this heterogeneity in preferences.

Waldfogel (2011) shows that quality in the music industry has not declined with general revenue decreases in the past decade. He uses various "best of" lists of the top albums in a certain time period to measure quality. Using such respected music review magazines as *NME*, *Spin*, *Mojo* and others I create a similar quality index. The reviewers are varied enough in intended consumers that any aggregate quality measures can range across a wide array of music preferences. These lists create a numerical ordering of the "top 30," "top 50," or "top 100" albums of the year; allowing for an exact, if somewhat subjective, ranking of the bands producing the highest quality products each year.

The festival must make different hiring decisions for bands that will be their products of greatest demand, the headliners, and those that will fill the smaller stages and less desirable times of the festival. The obvious explanation for the stratification in the popularity of the hired bands within festivals is differences in compensation required for each of the bands. I use a model of bilateral negotiation to explain the mutual hiring decision. Because it is a negotiation, it does not depend solely on demand decisions. For that reason, a separate analysis will measure the impact of various band characteristics on prominence within a festival. This model only includes bands which played a festival in a year, and determines what is the most important factor for a band's relative ranking in promotional material. Any differences in the demand results versus negotiation show where the festival must compromise between band characteristics they desire versus those they are able to obtain in order to maximize profit.

Commercially successful bands can demand greater fees. Therefore, if possible festivals would like to hire relatively unknown, less costly bands to occupy as many spots as they can within the lineup, particularly the lower placements in the order. The festival could justify this hiring decision by obtaining a reputation as a promoter of early quality, encouraging ticket purchases to discover new music products. This could benefit new bands as well despite the fact they will receive a lower fee than the more established bands. In this case the exposure to potential customers that comes from playing a music festival, coupled with the quality of the band, should contribute to increasing demand for the band in the ensuing years. The non-pecuniary benefit of increased reputation can compensate the band for being hired at a fee which is less than their value to the festival. The theoretical model in Section 3 creates an explanation for the stratified hiring decisions of music festivals.

This paper makes contributions in several areas. Beyond the initial level of hiring and prominence in a festival, these quality decisions can be viewed within the larger context of bundling. The music festivals discussed do not have the goal that every consumer will enjoy every band hired. In fact, considering the configuration of the festivals I review in this paper where many bands perform simultaneously, it is impossible to view more than a fraction of the shows in a given festival.[4] Therefore, the quality decisions of a music festival can be viewed as a bundling problem, hoping to reach a critical level of utility for each individual consumer while creating a horizontally diverse product which attracts consumers with a broad range of preferences. A unique contribution of this paper involves the way in which concerts are bundled. While consumers are usually assumed to know the characteristics of all of the bundled products, the theory model of this paper assumes there is an unknown element to the consumer in this bundle.

My primary focus is on decisions of quality by firms in the face of both horizontal and vertical differentiation and negotiable input costs. In addition to a simple model to explain the motivation, I test the determinants of quality choices in the festival industry empirically. The model in this paper, in conjunction with the empirical evidence, can explain why quality and cost are not always

[4]Concerts are played throughout each day of the festival with multiple performers playing simultaneously.

perfectly correlated. Results of this paper show that quality is important to music festivals. Nearly as important, however, is hiring inexperienced bands; explained by providing the same high level of quality without the corresponding high fees. The insights gained from the production of these music festivals can then be extended to other industries facing similar quality and cost negotiation decisions.

The remainder of this paper is organized as follows: Section 2 provides background on the music industry and input quality decision making. In Section 3 I create a theoretical model of festival demand, and Section 4 introduces the empirical models to be estimated. Section 5 relays the data and provides some initial summary statistics. Section 6 provides results and Section 7 concludes.

2.2 Background

Sustained success for a music festival in the United States is a recent development. Prior to the permanent launch of the Coachella Valley Music and Artists Festival in 2001, no American festival with the scale and impact of the large European festivals maintained an annual presence in a single location. Since the year 2000, there has been a considerable increase in the presence of massive music festivals in the United States. The four American festivals mentioned in this paper have all maintained a strong and increasing presence since their inception. To be sure, there have been a number of other festivals of comparable size that failed to achieve success during the same period and are no longer in existence, but the continued presence of these productions where none existed before seems to show a better understanding by the festival of how to hire the appropriate lineup for profitability. The hiring mix which these festivals use involves artists which vary widely in popularity and quality. An alternative explanation for failure could be derived from varied use of exclusive dealing. For example, no northeastern festival has managed to operate profitably. Potentially, bands won't agree to a restrictive exclusive dealing clause in the heavily populated area, thus eliminating the opportunity for profit.

The standard models of quality differentiation are usually written about in terms of a choice between high and low quality inputs and their difference in costs. These models take into account the effect on demand and cost at these different levels of quality, and assume firms make decisions accordingly. The music festival faces consumers with broad horizontal differentiation as described in Hotelling (1929). Each festival must also then contend with additional elements of vertical quality decisions determined in conjunction with these horizontal, or in this case genre choices, as explained in Shaked and Sutton (1987).

Jacobson and Aaker (1987) examine quality choices in the context of competition. Allowing for endogenous quality choice, firms can make different decisions in equilibrium. Through empirical tests they show quality to be associated with higher prices caused by a cost premium in production. Rhee (1996) models quality decisions in the face of unobservable consumer heterogeneity, showing that different product decisions can be made by firms facing the same emphasis on quality if preferences are unobservable.

Any analysis of music festivals must extend beyond the traditional theory of differentiation. The festival industry may be a unique case where bands of the highest recent quality, at least the quality measures available to this paper, are not perfectly correlated with the highest fees for performance. Prior popularity plays an important role, allowing for persistent demand despite a lack of quality in the near past. Evidence is available for this hypothesis. The correlation coefficient between receiving a rating from any of the quality measures for an album and having a top 200 album in sales in a given year is only .153. Additionally, the correlation coefficient for a quality measure and operating a top 100 tour by gross receipts in a year is only .075. The criteria for quality do not necessarily match the criteria for sales. Alternatively, the correlation between having a top 200 album and operating a top 100 tour is .408. This industry must be considered with these caveats, as well as the fact that the inputs a festival chooses cannot be treated as traditional inputs.

The closest industry to the music festival in terms of input decisions is probably a sports league with a "closed" supply of athletes. Firms must make decisions on the product they will generate based on the quality of the athletes they use and what they must pay them. Like a music festival these firms have to determine the optimal quality and pay that will maximize their profit. In this context, Fort and Winfree (2009) show that the relatively inelastic supply of athletes is important to how professional sports are operated, and quality decisions must be considered with this limit in mind. Professional athletic teams find it very difficult to replace their largest generators of demand, the highly skilled professional athlete, much as a music festival finds difficulty in replacing one of its headliners.

These decisions are also similar to that of a streaming video service, such as Netflix or Amazon

Prime. These services charge a fixed monthly or annual fee for unlimited viewing from their library of film and television. The clear objective is to provide, in any month, sufficient entertaintment value to the consumer to pay for the service. These services attempt to achieve this utility without the availability of many recent "blockbusters," or commercial success of tremendous popularity. The reason is similar to the music festival, higher licensing fees. Some combination of commercial successes with high licensing fees, and more obscure but cheaper films serve to achieve the necessary bundled utility.

The music festival is also an example of a firm that takes advantage of product bundling. As first noted in Stigler (1968) and extended in McAfee et al. (1989), under certain conditions a monopolist can maximize profits by exclusively selling bundles rather than individual products. This pure bundling can be utilized by music festivals because of the monopoly power they can exhibit. Each music festival uses an exclusivity clause to control the ability of participating bands to perform independently of the festival within close proximity to the festival. Combined with the somewhat transient nature of touring bands, the music festival has an effective monopoly on the local performance of the participating musicians. They can use this monopoly to force the consumer whose combined utility of performers is sufficiently high to purchase the right to view all of the performances within the festival in order to see the bands which are of interest to her.

The festival must create their bundled product with the intent to utilize either positive or negative correlation in the values of their performers. The fact that the consumer cannot view every performance dictates that the festival must attempt to create a negative correlation of values during a single time slot, when bands must compete for a consumer's attention, and positive correlation across different periods in the festival. The festival does wants the consumer to be able to have a clear favorite among the bands playing during any specific time, but many bands which they will enjoy over the entire festival. The profitability of bundling in this case can be addressed by Chen and Riordan (2013), who establish that given negative correlation between products or sufficiently limited positive correlation, bundling can be profitable. In this case the festival uses the existence of positive correlations within genres, as well as the negative correlations across some genres to attract an audience with diverse preferences.

This stands in stark contrast to the standard musical performance where a venue provides one or two primary bands with a considerably lower ticket price.[5] In this respect the music festival acts much like the examples of pure bundling firms provided by Adams and Yellen (1976). Additionally, the festivals may have an advantage in information when creating their bundle. The idea of using informational leverage and quality bundling as a signal is put forward by Choi (2003) to explain how a firm may use a well known high quality product with a newly introduced product to encourage the new product's purchase. This differs from my model in terms of music festivals using the new product as a cost efficient means of enhancing reputation, but the informational advantage of the firm is similar.

The inelastic supply means that festival producers cannot simply choose between inexhaustible quality differentiated inputs. Instead, while the festival decides on whom to hire the band must also be in agreement with the festival regarding their fee, taking into consideration their optimal touring plans. Connolly and Krueger (2006) review the concert hiring process, finding the artist gets much if not most of their revenue from touring the country and putting on concerts. Dependence on concerts as a revenue stream means important decisions must be made on how long, how often, and where each band tours.

Mortimer et al. (2012) document that concert revenue and the amount of time bands spend touring have increased in the period since file sharing began. Music festivals, and touring more broadly have become a substantially bigger business in the recent past. Beyond the typical employment of a touring band, festivals can cause a specific concern. Major festivals enact a stringent exclusive dealing clause for bands they hire. This clause prohibits musicians from playing again in the same region for several months around the festival dates. For this reason, some potential festival participants may choose to never accept a contract. Alternatively, some bands may find playing many festivals to be an optimal strategy. The decision making of the band must then be taken into account in the ensuing analysis.

Evidence exists that music is an experience good. Rob and Waldfogel (2006) find that ex-post valuations of albums often fall below ex-ante valuations of albums. They attribute this largely to simply growing tired of the music after it has been listened to. If the utility of music declines with further listening, recent quality should play an important role in attracting customers to see a live performance. Of course, there remains the possibility that listening to an album is a different

[5] For a comparison of music festival versus local venue ticket prices see Hiller (2011).

experience than seeing a live performance of the same music and the utility from each experience is not correlated.

I draw on the literature of quality differentiation, bundling, similar industries, and previous work on the music industry in placing this paper in context and creating a basis for my own extension of research. The music festival is unique in its production, however, and requires motivation that accounts for the differentiation in quality as well as the necessity of negotiation with inputs. A model to explain the quality decisions of the music festival from a demand perspective is the subject of the next section.

2.3 A Model of Festival Demand

It is illustrative to simplify the operations of a festival to a basic level in order to consider the festival's decision making process when hiring a band. This section explains the motivation for festivals choosing bands with varying popularity and quality characteristics. The next section presents an empirical model that determines what band attributes are important to the festival in hiring decisions.

A festival depends on an array of bands differing in popularity and genre to create its final product. Some of these bands are well known and most consumers will have a set expected utility for seeing them. Most are headliners, commercial successes that will create substantial demand for the festival. Other bands will be placed in time slots when the headliners are not playing or on smaller stages, and the utility from seeing these acts is more variable. These bands are not prominent or highly demanded, either due to little success or recent entry into the market. In the theoretical model I simplify this hierarchy of bands into two types, known and unknown, representing the commercially successful and those that have not yet achieved success. Unlike most bundling problems, the consumer does not know the quality of the unknown band's live performance, and depends on the hiring reputation of the festival to establish expected utility. Festivals will hire one of each of these types based on characteristics of the band and the fee they must pay in order to hire them.

Specifically, festival i books only two bands from the entire pool of potentials for its production in period t, with one consumer who is deciding whether she will purchase a ticket. Band k is known to the consumer and band n is unknown. Under these circumstances consumer l makes her decision understanding she will receive utility u^*_{likt}, unobserved by the festival, from the known band. Utility from the known band is increasing with the quality of band k, q_{kt}, in period t. The consumer then expects to receive u^*_{lint} from the unknown band which is dependent and increasing in the the past quality level of festival i, q_{it-1}. Ultimately, q_{it-1} is based on the reputation of the festival for hiring high utility unknown bands in previous periods, and is assumed to be equal to q_{nt-1} in this simple example. Implicit in this model is the assumption that the festival will not hire only headliners for the multi-day event, but optimizes profit by mixing known and unknown bands choosing quality of each band they hire rather than quantity. The consumer then buys the ticket if:[6]

$$u^*_{likt}(q_{kt}) + u^*_{lint}(q_{nt-1}) \geq p_{it} \tag{2.1}$$

For two bands of equal quality, expected utility is assumed higher in viewing a known band rather than an unknown. The festival must make their decision based on the desired level of quality for the known band, the level of quality they want to establish or maintain for the next period with the unknown band, and the fees they must pay for each type of band.[7] The known band, k is chosen from the set of known bands, K with a cost of Fee_{ikt}. The unknown band n is chosen from the set N, with a cost of Fee_{int}. Each fee is based on characteristics of the band, which will be discussed further in later sections. For now it will suffice to say that the fees of each band are determined by their levels of quality, q_{kt} and q_{nt}. Fee_{kt} is assumed higher than Fee_{nt} for two bands of the same level of quality, which combined with the utility assumption, are the primary reasons a festival has for hiring an unknown band. For any number of periods, T, festival i then solves the maximization problem:

$$\begin{gathered}\max_{q_{kt},q_{nt}} \sum_{t=1}^{T} p_{it} - Fee_{ikt}(q_{kt}) - Fee_{int}(q_{nt}) \\ s.t.\ u^*_{likt}(q_{kt}) + u^*_{lint}(q_{nt-1}) = p_{it}\ \forall t\end{gathered} \tag{2.2}$$

[6]Of course, there are other potential reasons for attending a festival. Consumers may get utility from going with others, status, or many other possibilities. This analysis focuses on the primary draw of a concert, the bands.

[7]There may also be complementarities between the known and unknown bands. This model is intended to provide a simple illustration and could be expanded with considerably more complex relationships.

The constraint for the festival assumes the price of the festival, p_{it}, is set based the sum of different consumer utility from known and unknown bands, with the goal of equalizing the marginal benefit of the consumer and the marginal costs of each type of band considering the fees are lower for unknown bands. In a single period model the festival will attempt to set their price equal to the combined utility the consumer derives from the known band and her expected utility based on the previous quality of the festival, and hire the unknown band that will accept the lowest fee possible. The reality of these festivals is different, as each decision must be made within the context of a repeated game of unknown length. Reputation becomes important in the repeated game, and the festival must then consider how their decision will impact revenue in the next period. For example, in the first period of a two period game the chosen quality level for band n will still have no effect on the customer's decision in period one but alters utility, and therefore profit, for period two. Solving for the first period of a two period game with no discounting yields:

$$\frac{Fee'_{ik1}(q_{k1})}{Fee'_{in1}(q_{n1})} = \frac{u^{*'}_{lik1}(q_{k1})}{u^{*'}_{in2}(q_{n1})} \tag{2.3}$$

The goal of the festival is to equalize marginal cost in the quality of the bands they hire with the marginal utility that will be provided to consumers. This allows the festival to set their price based on the optimized utility of the consumers, and maximize profit if they can reasonably predict the utility bands will provide. The capacity of a festival is set prior to hiring decisions, and determined by the limitations of the venue. Each festival in this study regularly sells out of tickets, so the model can easily be extended from a representative consumer to any number of consumers by assuming the festival attempts to set a price equal to the sum of consumer utility of all consumers at their capacity.

No functional form is assumed for how the band's fee or consumer utility respond to quality. Simple assumptions allow the conditions needed for this model to fit the observed hiring patterns of festivals. If consumer utility increases at a similar rate in the quality of known and unknown bands, and fees increase more quickly in quality for the known band, then festivals will tend toward higher quality among the bands they hire which are unknown, hiring known bands of lesser quality. The fee assumption is justified by the idea that among commercially successful bands, higher quality can demand a higher premium. In contrast, unknown bands have not demonstrated their quality translates to commercial viability, and are unlikely to be able to differentiate themselves greatly in price.

Additional changes can be made to allow utility to vary by consumer; reputation can depend on more than merely the past period, and allowances can be made for varying types of bands beyond known and unknown. The premise of this model still holds for festival motivation, and the next section establishes a practical model for understanding the negotiations between the festivals and their inputs, the bands.

2.4 Empirical Model Specification

The primary empirical objective of this paper is to determine how music festivals make their production decisions, and using that knowledge to explain how firms with varying costs contend with quality. This requires accounting for the criteria festivals use when making agreements with bands, as well as including those factors that a band would use in deciding on whether to perform at a festival. The empirical studies of this paper focus on the two relevant questions. First, I address what factors affect the likelihood of a band playing these music festivals and determine if recent quality is an important variable in deriving these probabilities. If the model of known versus unknown bands is correct, newer high quality bands should have a higher likelihood of participation. The touring patterns of many bands indicate that some control is necessary for time invariant behavior and varying festival conditions across years, and the panel dataset allows for fixed effects in band and year. Second, I find what is important in assigning prominence within a festival among those bands that are hired to participate. Beyond the quality measures I include various characteristics of bands that could plausibly affect the festival decision making.

2.4.1 Hiring Decisions

Two equations serve as the basis for the empirical study. The first is a profit function for any of the festivals in the sample, and the second is a decision function for each band. The reduced form expected marginal profit function, which is not observed, for a festival hiring a band is:

$$\begin{aligned}\pi^*_{ijt} =& Revenue^*_{ijt}(Experience_{jt}; Quality_{jt}; PastQuality_{jt}; Popularity_{jt}; PastPopularity_{jt}) \\ &- Fee^*_{ijt}(Experience_{jt}; Quality_{jt}; PastQuality_{jt}; Popularity_{jt}; PastPopularity_{jt}) \\ &+ \epsilon_{it}\end{aligned} \tag{2.4}$$

Where the expected marginal profit is for festival i hiring band j in period t. This function requires assumptions that follow the general structure of festival production. The firm creates the festival by procuring the space necessary, determining the dates, and then hiring the bands to fill the lineup. With capacity for customers and space for stages determined before booking the lineup, the number of bands which can be hired is exogenous and separate from the decision of which bands are hired. The assumption implies that all festival costs are fixed and there are no marginal costs to hire a band beyond the fee paid. In this model, revenue for the festival and the fees paid are dependent on the attributes of the band hired.

Before estimation I must specify the functional form of the band attributes on which the festival's marginal revenue from hiring a band depend. Marginal revenue is assumed to be linearly dependent on several characteristics:

$$\begin{aligned}Revenue^*_{ijt} =& \gamma_1 PriorFests_{jt} + \gamma_2 PriorFestRank_{jt} + \gamma_3 LastToured_{jt} + \\ & Quality_{jt}\Theta + Popularity_{jt}\Gamma + \epsilon_{it}\end{aligned} \tag{2.5}$$

The error term for the expected profit function is the same as that of marginal revenue for the festival. $PriorFests$ is a measure of the festival experience of a band in the last two years, used as a predictor of future demand. The festival is also likely to look at prior popularity of a band, so $PriorFestRank$ is the average previous ranking for a band if they played a festival within the last two years. The $LastToured$ variable measures how much time has passed since the band has last toured. $Quality$ is a vector of the various quality index variables used throughout the paper and their lag values, while $Popularity$ is a vector of the common measures of band popularity explained in the Data section, as well as lag variables for each.

When producing a festival the bands are the inputs, and they must benefit in order to agree to participate. The band's profit function, also not observed, is:

$$\begin{aligned}\pi^*_{jit} = &Fee^*_{ijt}(Experience_{jt}; Quality_{jt}; PastQuality_{jt}; Popularity_{jt}; PastPopularity_{jt}) \\ &- CostTouring^*_{jit} - OppCost_{jit} + \epsilon_{jt}\end{aligned} \tag{2.6}$$

Band j is paid the fee negotiated with festival i in period t. The costs of participating are both explicit in terms of the cost of touring in that year for the band, and implicit in the opportunity cost of playing the festival. Implicit costs include foregone revenue from concerts which they would have been able to play in the surrounding region if not for the exclusive deal required by the festivals.

The opportunity costs could vary considerably depending on the band, so a band fixed effect will serve as the individual opportunity cost variable. An individual fixed effect is necessary due to the differing habits of the wide range of bands in the data. Additionally, a year fixed effect measures whether the general opportunity cost changes over time, gauging the overall climate of the music touring industry. Touring decisions can vary by type of music played, prominence of the band, and whether the band is on hiatus or disbanded. Estimation without fixed effects rarely converged in tests in the Results section, likely indicating an incorrect specification.

In order for band j to be hired by festival i two conditions must hold. First, the band must be more profitable for the festival than any band not chosen, $-j$:

$$\pi^*_{ijt} \geq \pi^*_{i-jt} \tag{2.7}$$

Second, the profit to band j must be greater than or equal to its alternatives:

$$\pi^*_{jit} \geq 0 \tag{2.8}$$

In order to gain tractability I make a common economic assumption about the bands, that each will receive a fee equal to their explicit and implicit costs of playing, $\pi^*_{jit} = 0$. Equation 2.6 can now be substituted into Equation 2.4, eliminating the fee paid to the band and providing an equilibrium for band j to be hired if the function in Equation 2.9 satisfies profit maximization:

$$\pi^*_{ijt} = Revenue_{ijt} - CostTouring_{jit} - OppCost_{jit} + \epsilon_{it} - \epsilon_{jt} \tag{2.9}$$

The hiring of any band to participate in a festival must satisfy Equation 2.7. The difference in profit of a band playing a festival versus any others in the sample not hired is now:

$$\begin{aligned}\pi^*_{ijt} - \pi^*_{i-jt} =& Revenue_{ijt} - CostTouring_{jit} - OppCost_{jit} - Revenue_{i-jt} \\ &+ CostTouring_{-jit} + OppCost_{-jit} + \epsilon_{jt} - \epsilon_{-jt}\end{aligned} \tag{2.10}$$

The error term for the festival, ϵ_{it}, is differenced out for any year. With the assumption of a type 1 extreme value distribution for band error terms, this model can be estimated using a conditional fixed effects logit. The difference in profit between the chosen band and all others, $\pi^*_{ijt} - \pi^*_{i-jt} > 0$, is not observed. However, the dependent variable, whether or not a band played a festival in a given year, is equal to 1 for any band where this inequality holds and 0 otherwise. This specification means that observations lacking within group variation in the dependent variable are dropped.

2.4.2 Prominence within a Festival

The second part of the empirical results considers the prominence of each band. After all hiring decisions are made a festival must determine the ordering of bands within the festival, establishing which bands will play on the larger stages and be advertised heavily to attract consumers. The festival must make these decisions based on many of the same characteristics that are used in the hiring decision. Unlike the hiring decision the band does not have any input into this process. The model testing the determinants of prominence within a festival is similar to the festival's revenue function:

$$\begin{aligned}AveFestRank_{jt} =& \gamma_1 PriorFests_{jt} + \gamma_2 PriorFestRank_{jt} + \gamma_3 LastToured_{jt} \\ &+ Quality_{jt}\Theta + Popularity_{jt}\Gamma + \epsilon_{jt}\end{aligned} \tag{2.11}$$

The sample for this model is limited to those bands which have been hired by a festival in a given year. The dependent variable for estimation, $AveFestRank$, is the average rank in prominence of festival promotional material for a band in a given year. For that reason, no band fixed effects are included as the changing characteristics of bands from year to year should change the ranking. There is no reason to believe that any characteristic of a band that is time invariant should affect festival prominence. Additionally, there is no cost of touring included in this model as each band in this sample participates in a festival.

2.5 Data

In order to test what determines a band's likelihood of playing festivals, I created a data set of potential bands that could play these festivals each year. The bands which form this set are established by two sources. First, any band that has played in one of the five festivals examined is considered to be a potential performer. Additionally, each band which appears in one of the quality measures is included whether it has played a festival before or not. This establishes variation in quality among those that are hired by festivals versus those that are not. An overview of the variables used in this paper is available in Table 2.18.

Data on the festival lineups come from a variety of sources. Each of the observed festivals has a website with some archival history of past performances.[8] For most years of a festival's history there are options to order artists by their expected demand, with headliners coming first and bands with lesser demand in descending order. Where this ordering is not possible I accessed promotional posters from each year of the festival, noting prominence of name placement as a measure of expected demand. High demand headliners are listed first and in a larger font, while a decreasing font and less prominent position are used as the relevance of the band decreases. The process of determining a ranking is slightly subjective, but general distinctions can be made between the various classes of bands as determined by the festival's expected demand. Each year's lineup for all festivals was then manually checked against information on Songkick.com, a company which collects data on touring in the music industry. Within the data set Coachella first appeared in 2001. Bonnaroo, Austin City Limits, and Glastonbury all first took place in 2002, and Lollapalooza became a permanent fixture in Chicago in 2005. All festivals were then held annually except Glastonbury, which was not produced in 2006.[9]

Quality measures are similar to those used in Waldfogel (2011), but are annual lists of the highest rated albums produced in the preceding year rather than a decades long examination.

[8] Austin City Limits: aclfestival.com; Bonnaroo: bonnaroo.com; Coachella: coachella.com; Lollapalooza: lollapalooza.com; Glastonbury: glastonburyfestivals.co.uk. All last Accessed: 10/11/2011.

[9] Glastonbury is a festival in the United Kingdom comparable in size, attendance, and hiring structure to the other four, included to increase the sample and improve estimates. Because it is outside of the US all specifications were also run with Glastonbury excluded, and the results were not qualitatively different.

These lists are produced by respected music themed magazines and websites, and represent a wide range of musical preferences.[10] In each of the lists the top 30, 40, 50 or 100 albums of the year ranked by a quality measure such that $q_1 > ... > q_n$, where q_i is the quality of album i. All of the lists are from publications or websites produced in the United States or the United Kingdom. For the purpose of this paper the integer value of the ranking of an album, and more importantly the band which produced the album in each of the seven publications is recorded.[11] Most bands do not appear in any of these rankings in a given year, and in this case a zero is assigned to the band for this publication-year. All years from 2001-2010 are included for these lists of top albums, with the exception of *Pitchfork* in 2001.

Preferences for music are horizontally differentiated. For all of the top album lists except for *Metacritic* and *Besteveralbums*, the editorial staff decide on their opinions of the quality of the year's production of albums and their relative rankings. This means that rankings vary across publications because of the varied preferences in music production. Total consensus of the highest quality music producers in a given year is an impossibility. This subjectivity is not a problem. In fact, some heterogeneity in the rankings is crucial to examining how festivals make their decisions as consumers are similarly heterogeneous. The difference across the various measures of quality will be used to help determine which of the top album lists chosen have the biggest effect on festival hiring.

Metacritic creates a score based on a 100 point scale for albums released. They do so with a process that "curates a large group of the world's most respected critics, assigns scores to their reviews, and applies a weighted average to summarize the range of their opinions."[12] Different weights are assigned to different critics based on their perceived importance and stature within the industry, as determined by *Metacritic*. The resulting rating is a weighted index of the best albums of the year as chosen by many publications and critics, easily ranked by their numerical score. Presumably, *Metacritic* rankings should be closest in preferences to the consumer base as a whole.

Besteveralbums is different in that the retrospective rankings are not absolutely fixed at the

[10] The year-end lists are produced by *BestEver.com*, *Metacritic.com*, *Pitchfork.com*, *Mojo*, *NME*, and *Spin*.
[11] I manually collected data on rankings from publication websites in order to ensure accuracy.
[12] http://www.metacritic.com/about-metascores, Accessed 10/11/2011.

end of the given year.[13] The firm allows users to submit their own list of the top albums and aggregates the results to create their list of the top 100 albums. Because of the possible fluidity of these rankings, their effect on festival hiring decisions may vary from the other quality measures. Specifically, it may be expected that as bands gain prominence their relative ranking on a changing list may rise, creating a positive bias on the relationship between these rankings and festival appearances. This bias should be less important in more recent years as there may not yet be the requisite time needed for any correction in popularity.

There is still the possibility that festival lineup decisions are driven by demand considerations other than quality. Album sales by a band is an obvious indicator of some degree of popularity. The "Billboard Top 200" is a list of the top 200 albums sold in a year, as determined by Nielsen Soundscan.[14] Soundscan uses point of service sales data in the US, as well as digital sales for the years following the introduction of online retailers like iTunes. For each year in the sample period an indicator, $TopAlbum$, is applied to any band which reaches the top 200 in album sales.

Additionally, the top touring bands may have an increased likelihood of being hired by festivals. Pollstar ranks the top 100 touring bands of the year on gross revenue. These are the bands able to pull in large crowds at high ticket prices, so they can presumably demand a high fee for appearance in a festival. This means that despite high demand, appearance on this list should not guarantee a considerably higher probability of playing one of the festivals observed. I have included an indicator, $TopTour$, for the list of the top 100 touring bands from 2002-2007. This time frame should be sufficient to determine if the presence of a successful touring band substantially affects other coefficients.

The touring habits of bands differ significantly depending on the band. In order to account for the length of time between tours I have constructed a series determining the touring habits of bands outside of a festival in the given year. From this information I created a variable, $LastToured$, to express when the band last toured. For example, if a band toured in 2001 and not again until 2004, the $LastToured$ variable would be equal to three in 2004. Of course, this variable is not entirely accurate for bands that toured before 2001. For that reason I also include a variable for the first tour of a band in the sample, $FirstTour$, which would be the first tour for any new band but only

[13] Top 100 Lists used from each year in the dataset, Accessed 7/14/2011.

[14] Bands included in the festival database were again manually cross-referenced against the Billboard lists available online.

the first tour during the observed period for bands that existed before the beginning of the dataset.

The touring data is again from Songkick.[15] Construction of the touring variable required a threshold number of performances to be considered as having toured in a given year. The threshold used is five performance dates, excluding the festivals examined in this paper, over different cities. Different cities are required because local bands, bands not playing a regional or national tour, may simply play repeatedly in their home city without gaining any national popularity. Localized performances mean these bands are unlikely to attract attention from any festivals outside of their immediate vicinity. In fact, while constructing the data set it was impossible not to notice that a vast majority of bands which were not considered to be touring in a given year and still played a festival in that year frequently performed in the city of the festival they participated in.

2.5.1 Summary Statistics

Information on the observed festivals through the sample years is available in Table 2.1. The average number of total bands playing the five festivals each year from 2003-2011 is 555.3. The years 2001 and 2002 are excluded from the summary statistics as the creation of lag variables requires their exclusion from the sample. This number increases steadily, but not monotonically throughout the time period with a minimum of 372 bands in 2004 and a maximum of 747 in 2011. In the years 2003, 2004, and 2006 only four of the five festivals are operational. The average number of bands per festival also increases substantially over the period with a minimum of 92.6 in 2005 and a maximum of 149.5 in 2011. From 2003 through 2006 the average number of bands per festival is 95.78, and 2007 through 2011 that statistic is 134.9. Clearly, these festivals are expanding in size through the period analyzed.

Table 2.2 shows the correlation matrix for the six publications and measures used to create the quality index. There is certainly considerable overlap, but inclusion in one of the lists does not guarantee inclusion in any other. Correlation coefficients are generally close to a mean of .3 with a maximum of .36 in any pairwise match. There are 1218 observations in which a band received inclusion in only one measure, 318 observations with inclusion in two, 156 with inclusion in three, 82 with inclusion in four, 42 with inclusion in five, and only 30 with inclusion in all six.

[15] Unfortunately, I was unable to locate a large database of what bands toured by year. Each band was researched on Songkick and their touring dates inspected by year.

The sample has been limited in Table 2.3 to only include the top 25 ranked albums of each year in each measure. The limitation is imposed in order to see how much inclusion consensus is achieved if all lists have an equal number of albums in each year. Clearly, the correlation is generally greater between each measure in this case, reaching a maximum of .48. However, the increases in the correlation coefficient are not sufficient to consider the measures to be highly correlated, now averaging about .35. Consensus on top albums is difficult to come by among these measures, indicating coverage of many possible values over the horizontal quality dimension.

Table 2.1: Number of Performers in Festivals

Year	**ACL**	**Bon**	**Coach**	**Lol**	**Glast**	**Total**	**Mean (Active Festivals)**
2003	122	67	81	0	117	387	96.75
2004	98	77	85	0	112	372	93
2005	110	80	95	58	120	463	92.6
2006	115	86	95	107	0	403	100.75
2007	121	101	120	148	141	631	126.2
2008	126	114	133	118	148	639	127.8
2009	122	132	142	108	147	651	130.2
2010	121	152	145	127	160	705	141
2011	123	160	171	138	155	747	149.4

Table 2.2: Correlation Matrix for Inclusion in Quality Measures

	Bestever	**Mojo**	**Pitchfork**	**Spin**	**NME**	**Metacritic**
Bestever	1					
Mojo	0.26	1				
Pitchfork	0.27	0.21	1			
Spin	0.33	0.27	0.34	1		
NME	0.34	0.36	0.23	0.33	1	
Metacritic	0.23	0.29	0.32	0.26	0.196	1

Table 2.3: Correlation Matrix for Inclusion in Top 25 Quality Measures

	Bestever	**Mojo**	**Pitchfork**	**Spin**	**NME**	**Metacritic**
Bestever	1					
Mojo	0.34	1				
Pitchfork	0.32	0.19	1			
Spin	0.37	0.25	0.35	1		
NME	0.48	0.41	0.26	0.36	1	
Metacritic	0.26	0.24	0.32	0.29	0.23	1

In any given year an average of 2.3 percent of bands in the sample will have an album in the

Billboard Top 200, and 1.4 percent will have a top 100 grossing tour. The average band can expect to have an album included in at least one of the quality measures 6.7 percent of the time with a mean number of these publications recognizing them of 1.64 for each album rated. Additionally, the average band will play a festival in 12.6 percent of the years in the sample, with a mean of 1.26 festivals played in each of those years in which they participate. Bands in the sample are actively touring for 48.6 percent of the available years. The time bands do not tour is composed of bands not yet formed, no longer performing, or simply taking a hiatus from touring.

2.6 Results

The model in Section 2.4 represents the negotiation process leading to hiring decisions between festival and band, and has an indicator for each band to determine whether they played a festival in a given year as its dependent variable. This model is then estimated with a conditional fixed effect logit. The marginal effects from the logit are available in the first table referenced in each section. The marginal effects will be referenced in the text for ease of interpretation. The corresponding raw results can be found in the second table of each section. Quality is measured with a simple variable indicating whether a band is included in one of the lists ($Rating$) in a given year in the models in Section 2.6.1, and then measured by how many quality ratings ($TotalRatings$) a band is included in in Section 2.6.2. As mentioned above, data on the top 100 tours is available for only five years in the sample. For this reason, the $TopTour$ indicator is included as a robustness check where each model is tested with a reduced five year sample.

The first column of each table provides the results for a baseline model excluding the cost of touring, $TourCosts$, which the second column includes. The third column adds to the baseline with an indicator for the first time a band receives a rating ($FirstRating$) and whether they have ever played a festival before ($EverFest$). The fourth column adds two interaction terms that attempt to determine the importance of quality ratings in conjunction with other potentially relevant band characteristics ($FirstRating * YearsToured, Rating * TopAlbum$). All results referenced in the paper are from the model in column 4 when each column provides similar results. I discuss any significant outliers by referencing which of the models they are in.

Results of the prominence models determining the average ranking of bands playing festivals are available in Tables 2.12 - 2.15. These models have the average rank of all of the festivals a band participates in a given year. This rank is taken from the prominence of the band in the festival's promotional material. These models are estimated by linear regression reflecting the assumption that the error term for the average ranking of bands in a festival is normally distributed. Of course, this specification can lead to rank predictions that are negative, but the large sample size and the fact that this is not a prediction model should help to negate these concerns. Additionally, these rankings are not exact, but intended as a general guide to prominence. Each of these tables contains only three columns as there is no consideration of the cost to the band of touring made in festival promotion.

2.6.1 Models using a Quality Indicator

Table 2.4 provides estimates for the model using a simple measure of quality, whether a band is included in one of the quality measures. Inclusion in at least one quality measure, represented by the variable *Rating*, clearly increases the probability of playing a festival. The primary measure of popularity, *TopAlbum*, provides a similar effect. It is important to note the duration of the effect of each of these variables.[16] In the initial year a quality rating does not quite match the effect of a top album, but the coefficient on the first lag of *Rating* nearly matches that of *TopAlbum* alone. With the effects from each of the quality lag variables, the increased probability is sustained over several years and the combined impact is greater than that of a top album.

The marginal effects give the percentage change in likelihood of playing a festival that comes with a change in the specified variable when compared with the mean band. The average band plays a festival in 12.6 percent of the given years, and as an example a band that receives a quality rating will be about 16.5 percent more likely to play a festival in that year, with lagging effects from the quality ratings in the future. So with all else constant this band would successfully negotiate with a festival 29.1 percent of the time. Production of a top 200 album has a definitive probability increase of approximately 25 percent in the same year, but lagging effects are never significant or substantial. This shows that while having a successful album is certainly more important than a quality measure in the first year, quality inclusion has a lasting and ultimately more substantial

[16] A lead variable was also tested for the Rating variable, but never proved important. I also tested further lags for the TopAlbum variable, but none were significant.

Table 2.4: Hiring Models with an Indicator for Quality - Marginal Effects

	(1) Fest	(2) Fest	(3) Fest	(4) Fest
Rating	0.125***	0.112***	0.170***	0.173***
	(0.04)	(0.03)	(0.05)	(0.05)
Rating(t-1)	0.257***	0.201***	0.251***	0.250***
	(0.02)	(0.02)	(0.02)	(0.02)
Rating(t-2)	0.082***	0.093***	0.085***	0.084**
	(0.02)	(0.02)	(0.03)	(0.03)
AveRank	0.001	0.002	0.002	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
TopAlbum	0.236***	0.182***	0.261***	0.273***
	(0.05)	(0.03)	(0.04)	(0.05)
TopAlbum(t-1)	0.033	0.036	0.056	0.061
	(0.03)	(0.04)	(0.05)	(0.05)
PriorFests	-0.029***	-0.035***	0.058***	0.057***
	(0.01)	(0.01)	(0.01)	(0.01)
PriorFestRank	-0.002***	-0.002***	-0.003***	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)
LastToured	-0.148***	-0.061***	-0.077***	-0.076***
	(0.01)	(0.02)	(0.01)	(0.01)
FirstTour	-0.101***	-0.220***	-0.212***	-0.210***
	(0.01)	(0.02)	(0.02)	(0.02)
TourCosts		-0.497***	-0.497***	-0.500***
		(0.01)	(0.05)	(0.05)
FirstRating			-0.112**	-0.03
			(0.04)	(0.03)
EverFest			-0.387***	-0.388***
			(0.02)	(0.02)
FirstRating*YearsToured				.046*
				(0.018)
Year FixedEffects	Yes	Yes	Yes	Yes
Band FixedEffects	Yes	Yes	Yes	Yes
Observations	19327	19327	19327	19327

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable, Fest, is an indicator for inclusion in any festival.
The marginal effect can be interpreted as the percentage change effect on
on hiring probability derived from a one unit change in the variable.
Because the model in Column 4 contains interaction terms the
marginal effect and standard errors are manually computed.

Table 2.5: Hiring Models with an Indicator for Quality - Raw Results

	(1) Fest	(2) Fest	(3) Fest	(4) Fest
Rating	0.677***	0.575***	0.687***	0.667***
	(0.171)	(0.173)	(0.191)	(0.198)
Rating(t-1)	1.252***	1.182***	1.043***	1.041***
	(0.0914)	(0.0927)	(0.0960)	(0.0962)
Rating(t-2)	0.465***	0.464***	0.339***	0.337**
	(0.0973)	(0.0987)	(0.103)	(0.103)
AveRank	0.00907	0.00892	0.00843	0.00829
	(0.00528)	(0.00533)	(0.00550)	(0.00556)
TopAlbum	1.150***	1.068***	1.097***	1.038***
	(0.200)	(0.200)	(0.205)	(0.235)
TopAlbum(t-1)	0.197	0.171	0.224	0.244
	(0.198)	(0.200)	(0.203)	(0.207)
PriorFests	-0.185***	-0.160***	0.233***	0.231***
	(0.0385)	(0.0390)	(0.0438)	(0.0439)
PriorFestRank	-0.00973***	-0.00981***	-0.0135***	-0.0135***
	(0.00106)	(0.00107)	(0.00108)	(0.00108)
LastToured	-0.950***	-0.278***	-0.309***	-0.308***
	(0.0295)	(0.0577)	(0.0574)	(0.0574)
FirstTour	-0.807***	-0.924***	-0.939***	-0.929***
	(0.0770)	(0.0778)	(0.0807)	(0.0810)
TourCosts		-2.283***	-2.008***	-2.017***
		(0.182)	(0.177)	(0.177)
FirstRating			-0.472**	-0.776**
			(0.167)	(0.267)
EverFest			-1.857***	-1.858***
			(0.0941)	(0.0941)
FirstRating*YearsToured				0.113
				(0.0731)
Rating*TopAlbum				0.185
				(0.332)

impact. The implication of these results is that festivals see popularity in an individual year from a top selling album as important in that year, but the quality measures are a better indication of continued success in the following years. These results indicate that to some extent unproven quality can be substituted for commercial success in the hiring process.

The variables measuring band characteristics show that once quality and album sales are accounted for, relatively unknown bands are more likely to be hired for a festival. The $EverFest$ variable shows that bands that have played a festival before are significantly less likely to be hired for a festival in the current year than those that have not, on the order of approximately 39 percent. Although the relative unknown appears more likely to be hired, the first inclusion in a quality measure, the $FirstRating$ variable, either does not indicate unknown status or acts to counter that possibility. Indeed, the first inclusion in a quality measure may have a negative impact on that same probability.

If a band is not unknown, festival experience, represented by $PriorFests$ increases the likelihood of being hired. In the first two columns of Table 2.4 the number of prior festivals played in the past two years has a negative impact on festival probability. This is reversed in columns 3 and 4 as $EverFest$ in included in the model, proving that among the bands that have played a festival, those that play more have an increased likelihood of being hired again. The $PriorFestRank$ variable further reinforces this point. For those bands that have played festivals before, having a lower rank is equivalent to a more prominent position in promotional material. The explanation for this difference comes from the known versus unknown model. Bands unknown to the consumer at the time of hiring will accept a lower fee, and if chosen wisely will have a significant positive impact on the festival's reputation. Among bands known to consumers festivals must carefully choose who is hired, leaving those with more experience and proven demand much more likely to be chosen.

The band activity variables show that although being unknown to final consumers increases the likelihood of being hired, being inactive certainly decreases it. The $TourCosts$ variable shows the impact of the hiring probability of a band which did not tour in that year, excluding any festivals. The marginal estimates of this indicator show that all else equal, the touring costs of an inactive band decrease the likelihood of a band playing a festival by 50 percent. Additionally, $LastToured$ estimates show that each year since the last year a band toured decreases the likelihood of a band being hired by over seven percent. Of the two interaction variables included in column 4, only one is significant at the five percent level.[17]

2.6.2 Models using Total Inclusion in Quality Measures

Table 2.6 presents the marginal effects for models which use the total number of quality measures an album is included in, represented by the variable $TotalRatings$. The results look similar to the simple indicator model. Again, relative unknowns are more likely to be hired, presumably due to the fact that they can be paid a lower fee. But as in the last section, bands that are hired by a festival in previous years are more likely to be hired again if they were well received and prominently promoted by each festival they participated in. Additionally, estimates on the $FirstTour$ variable show that there is a limit to the increase in probability of hire for an unknown band. A band on its first national tour is significantly less likely to be included in a festival with a decrease of about 21 percent, all else equal. The fact that a band is touring for the first time in the sample makes it difficult for a festival to evaluate their potential quality and fit for hiring.

An additional interaction variable is included in column 5, and the estimate shows that a band that has played a festival before is 45 percent more likely to be hired in a given year if they have an album also included in a quality measure. If accurate this effect shows that quality is quite important to the experienced band, with a quality rating adding tremendously to the probability of hiring. This result seems to indicate that quality can also be a subsitute for commercial success with experienced bands as well. The cost of touring for a band which does not go on a national tour outside of a festival they played is similar to the model in Section 2.6.1, with a 50 percent decrease in the likelihood of being hired all else constant.

The estimates on quality measures show a smaller increase in likelihood for inclusion in a single publication than was true of the previous model of simple inclusion. For each additional quality publication an album is included in there is a corresponding probability increase over a band with no albums of about six percent in the first year, ten percent in the second year, and four percent in the third year, all statistically significant. This means that the 30 bands with an album in all six measures are 36 percent more likely to be hired in the first year, 60 percent in the second year, and 24 percent in the third year compared to a band with no album in any measure. Inclusion

[17]Due to problems interpreting marginal effects with interaction terms, estimation with interaction terms is done by manually coding the derivative and using the delta method for standard errors

Table 2.6: Hiring Models with Total Quality Inclusions - Marginal Effects

	(1)	(2)	(3)	(4)	(5)
	Fest	Fest	Fest	Fest	Fest
TotalRating	0.043***	0.052***	0.061***	0.060***	0.060***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
TotalRating(t-1)	0.078***	0.102***	0.102***	0.102***	0.102***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
TotalRating(t-2)	0.032***	0.046***	0.040***	0.040***	0.040***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
AveRank	0.002***	0.002**	0.003**	0.003**	0.003**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TopAlbum	0.232***	0.181***	0.260***	0.273***	0.243***
	(0.05)	(0.03)	(0.04)	(0.05)	(0.05)
TopAlbum(t-1)	0.032	0.037	0.056	0.062	0.062
	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)
PriorFests	-0.029***	-0.036***	0.057***	0.057***	0.057***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
PriorFestRank	-0.001***	-0.002***	-0.003***	-0.003***	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LastToured	-0.149***	-0.061***	-0.078***	-0.077***	-0.077***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
FirstTour	-0.102***	-0.224***	-0.215***	-0.213***	-0.214***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
TourCosts		-0.499***	-0.499***	-0.501***	-0.501***
		(0.01)	(0.05)	(0.05)	(0.05)
FirstRating			-0.107**	-0.177***	-0.164*
			(0.04)	(0.05)	(0.08)
EverFest			-0.387***	-0.388***	-0.389***
			(0.02)	(0.02)	(0.02)
FirstRating*YearsToured				0.048*	.048*
				(0.019)	(0.0191)
Rating*TopAlbum				0.059	0.053
				(0.08)	(0.139)
Year FixedEffects	Yes	Yes	Yes	Yes	Yes
Band FixedEffects	Yes	Yes	Yes	Yes	Yes
Observations	19327	19327	19327	19327	19327

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable, Fest, is an indicator for inclusion in any festival.
The marginal effect can be interpreted as the percentage change effect on
on hiring probability derived from a one unit change in the variable.
Because the model in Columns 4 and 5 contain interaction terms the
marginal effect and standard errors are manually computed.

Table 2.7: Hiring Models with Total Quality Inclusions - Raw Results

	(1)	(2)	(3)	(4)	(5)
	Fest	Fest	Fest	Fest	Fest
TotalRating	0.275^{***}	0.241^{***}	0.248^{***}	0.245^{***}	0.243^{***}
	(0.0519)	(0.0523)	(0.0541)	(0.0550)	(0.0550)
TotalRating(t-1)	0.507^{***}	0.472^{***}	0.414^{***}	0.414^{***}	0.414^{***}
	(0.0416)	(0.0419)	(0.0429)	(0.0430)	(0.0430)
TotalRating(t-2)	0.209^{***}	0.211^{***}	0.163^{***}	0.163^{***}	0.162^{***}
	(0.0435)	(0.0444)	(0.0456)	(0.0456)	(0.0456)
AveRank	0.0122^{***}	0.0110^{**}	0.0131^{**}	0.0126^{**}	0.0127^{**}
	(0.00351)	(0.00354)	(0.00410)	(0.00412)	(0.00412)
TopAlbum	1.138^{***}	1.057^{***}	1.090^{***}	1.011^{***}	1.010^{***}
	(0.198)	(0.199)	(0.204)	(0.234)	(0.234)
TopAlbum(t-1)	0.195	0.176	0.222	0.249	0.248
	(0.197)	(0.199)	(0.203)	(0.207)	(0.207)
PriorFests	-0.191^{***}	-0.166^{***}	0.229^{***}	0.226^{***}	0.227^{***}
	(0.0390)	(0.0395)	(0.0443)	(0.0443)	(0.0443)
PriorFestRank	-0.00952^{***}	-0.00961^{***}	-0.0134^{***}	-0.0134^{***}	-0.0134^{***}
	(0.00106)	(0.00107)	(0.00108)	(0.00108)	(0.00108)
LastToured	-0.958^{***}	-0.283^{***}	-0.313^{***}	-0.312^{***}	-0.312^{***}
	(0.0295)	(0.0578)	(0.0575)	(0.0575)	(0.0575)
FirstTour	-0.825^{***}	-0.943^{***}	-0.955^{***}	-0.945^{***}	-0.948^{***}
	(0.0769)	(0.0777)	(0.0806)	(0.0808)	(0.0809)
TourCosts		-2.292^{***}	-2.018^{***}	-2.027^{***}	-2.027^{***}
		(0.182)	(0.177)	(0.178)	(0.178)
FirstRating			-0.449^{**}	-0.774^{**}	-0.726^{**}
			(0.157)	(0.259)	(0.261)
EverFest			-1.857^{***}	-1.858^{***}	-1.864^{***}
			(0.0941)	(0.0941)	(0.0943)
FirstRating*YearsToured				0.118	0.0911
				(0.0726)	(0.0757)
Rating*TopAlbum				0.237	0.243
				(0.326)	(0.327)
EverFest*Rating					0.837
					(0.698)

in any publication means a substantial increase in aggregate hiring probability across three years. Additionally, these results indicate that although consensus is difficult to come by when measuring music quality, the more unanimous the high opinion of a band's quality the more likely a known band is to be hired. Having a top selling album provides an increase in likelihood which is similar to that in the previous model, with an effect of about 25 percent in the year of that album, diminishing rapidly in following years.

2.6.3 Models Including Touring Data

The above models have not accounted for the possibility that a band being in the top 100 in gross touring, $TopTour$, may have some impact on festival hiring decisions. Data on touring is available from 2002-2007, so both types of models from the previous two sections are tested in those years. In Tables 2.8 and 2.10 the marginal estimates from these models are available. Both have similar results to the models excluding touring variables. Estimates of inclusion in a quality measure, as seen by *Rating* and its lag variables, show a slightly higher increase in probability of playing a festival when compared to the models not accounting for top tours. The same is true for the $TotalRating$ model and its lag variables. Other differences include an increase in the positive effect of having a top 200 album and the lag of that variable in each model, and a more substantial negative effect for the touring costs if a band does not operate a tour that is independent of any festival in a given year. Including a top tour indicator as a robustness check does not discount the effects of quality seen in the above sections, and in fact may increase their magnitude.

In each model having a top tour appears to mean a higher likelihood of being hired by a festival in the same year. The effect is slightly larger in the model using $TotalRatings$ seen in Table 2.10 than in the simpler *Rating* model in Table 2.8. Statistical significance is a question though, as the estimate never rises above a five percent significance level and is insignificant in most models. Any positive effect is then negated by a considerable decrease in the same probability the next year, seen as the coefficient on $TopTour(t-1)$. The decrease is approximately 22 percent in each of the two models and is statistically significant. This result seems counterintuitive on its face, as both the quality measures and top album lag estimates are positive. The touring variable is slightly different. It indicates a band having one of the 100 highest grossing tours. These bands are able to command high ticket prices and have little difficulty in generating revenue. Their fee to play a

Table 2.8: Hiring Models with an Indicator for Quality and Tour Indicators - Marginal Effects

	(1) Fest	(2) Fest	(3) Fest	(4) Fest
Rating	0.147**	0.135**	0.171*	0.178*
	(0.06)	(0.05)	(0.07)	(0.07)
Rating(t-1)	0.288***	0.224***	0.299***	0.298***
	(0.04)	(0.03)	(0.04)	(0.04)
Rating(t-2)	0.113***	0.126***	0.153***	0.153***
	(0.03)	(0.03)	(0.04)	(0.04)
AveRank	0.001	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
TopAlbum	0.271**	0.202***	0.313***	0.317***
	(0.09)	(0.05)	(0.07)	(0.07)
TopAlbum(t-1)	0.122	0.123	0.224*	0.229*
	(0.08)	(0.07)	(0.09)	(0.09)
PriorFests	-0.101***	-0.139***	0.002	0.002
	(0.01)	(0.02)	(0.02)	(0.02)
PriorFestRank	-0.002***	-0.003***	-0.006***	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)
LastToured	-0.118***	-0.030	-0.050**	-0.050*
	(0.01)	(0.02)	(0.02)	(0.02)
FirstTour	-0.079***	-0.221***	-0.218***	-0.218***
	(0.01)	(0.03)	(0.03)	(0.03)
TopTour	0.119	0.112	0.197*	0.196*
	(0.08)	(0.07)	(0.10)	(0.10)
TopTour(t-1)	-0.101***	-0.269**	-0.228**	-0.224**
	(0.03)	(0.10)	(0.08)	(0.08)
TourCosts		-0.530***	-0.541***	-0.542***
		(0.02)	(0.08)	(0.08)
FirstRating			-0.037	-0.018
			(0.06)	(0.13)
EverFest			-0.478***	-0.479***
			(0.04)	(0.04)
FirstRating*YearsToured				0.007
				(0.03)
Year Fixed Effects	Yes	Yes	Yes	Yes
Band Fixed Effects	Yes	Yes	Yes	Yes
Observations	5705	5705	5705	5705

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable, Fest, is an indicator for inclusion in any festival. The marginal effect can be interpreted as the percentage change effect on on hiring probability derived from a one unit change in the variable.

Table 2.9: Hiring Models with an Indicator for Quality and Top Tour Indicators - Raw Results

	(1)	(2)	(3)	(4)
	Fest	Fest	Fest	Fest
Rating	0.824**	0.704**	0.692*	0.664*
	(0.262)	(0.264)	(0.294)	(0.306)
Rating(t-1)	1.445***	1.340***	1.264***	1.264***
	(0.156)	(0.159)	(0.167)	(0.169)
Rating(t-2)	0.655***	0.653***	0.619***	0.618***
	(0.158)	(0.161)	(0.170)	(0.171)
AveRank	0.00443	0.00358	0.00414	0.00459
	(0.00768)	(0.00777)	(0.00821)	(0.00832)
TopAlbum	1.337***	1.224***	1.357***	1.284**
	(0.353)	(0.358)	(0.369)	(0.442)
TopAlbum(t-1)	0.688	0.646	0.926*	0.948*
	(0.392)	(0.401)	(0.400)	(0.408)
PriorFests	-0.693***	-0.636***	0.00671	0.00637
	(0.0809)	(0.0819)	(0.0919)	(0.0919)
PriorFestRank	-0.0130***	-0.0137***	-0.0248***	-0.0248***
	(0.00234)	(0.00237)	(0.00256)	(0.00256)
LastToured	-0.812***	-0.138	-0.203*	-0.202*
	(0.0477)	(0.0799)	(0.0827)	(0.0828)
FirstTour	-0.649***	-0.927***	-0.969***	-0.968***
	(0.123)	(0.129)	(0.139)	(0.139)
TopTour	0.674	0.579	0.804	0.802
	(0.388)	(0.402)	(0.414)	(0.413)
TopTour(t-1)	-0.943*	-1.116**	-1.050*	-1.028*
	(0.410)	(0.424)	(0.436)	(0.442)
TouringCosts		-2.429***	-2.187***	-2.191***
		(0.250)	(0.252)	(0.253)
FirstRating			-0.150	-0.221
			(0.259)	(0.440)
EverFest			-2.610***	-2.609***
			(0.178)	(0.178)
FirstRating*YearsToured				0.0291
				(0.129)
Rating*TopAlbum				0.198
				(0.638)

festival is then high because of their outside option as a well-known band. The high fee means that a festival expects their marginal revenue from hiring the band does not exceed the fee sufficiently to justify their hiring over a lower fee band in the year following the top 100 tour. The second year effect is likely not a lack of demand, but an inability to reach a mutually profitable agreement.

2.6.4 Prominence within a Festival

In order to get further insight into what band characteristics are important to a festival, I reduce the sample to those bands which play a festival in a given year and find what is important for prominence in the lineup. This sample is limited to those bands which were hired, so there is no problem of negotiation between festival and band. This model can be seen as a clearer look into how the festival anticipates demand, whereas the earlier models had to account for negotiations with and decisions by the bands as inputs. The dependent variable is the average festival rank, where a lower number means a more prominent position in the festival. Negative coefficient estimates then indicate that the given attribute increases a band's prominence or lineup "rank," while a positive coefficient predicts a decreasing effect.

Tables 2.12 and 2.13 provide the results for the model of Equation 2.11 with quality measured as by $Rating$ and $TotalRatings$, respectively. Although quality increases the hiring probability in the same year as the ratings, these coefficients show that quality ratings have little to no impact on prominence. The timing of the ratings may play a role in this, as ratings are published at the end of each year and the festivals are all produced beforehand. The festival would then be hiring these bands with some knowledge of their quality and expecting they will enhance the reputation of the festival in future periods, but without much hope of the band increasing demand for the current period. The ensuing two periods after a rating show this to be true, as the estimates are significant and have a more substantial impact in both the first and second lag variables. Results in Tables 2.12 and 2.13 make it clear that inclusion in additional publications does not appear to be as important as they were for hiring probability. The first lag in each model, the most important period, shows an estimate of rank increase in this model is about 9 using $Rating$, with the corresponding $TotalRating$ coefficient having an effect of only 3.7 in the same period in Table 2.12.

Confirming the lesser importance of quality ratings are the top album indicators. Without an

Table 2.10: Hiring Models with Total Quality Inclusions And Top Tour Indicators - ME

	(1) Fest	(2) Fest	(3) Fest	(4) Fest
TotalRating	0.046***	0.064***	0.070**	0.069**
	(0.01)	(0.02)	(0.02)	(0.02)
TotalRating(t-1)	0.091***	0.129***	0.140***	0.140***
	(0.01)	(0.02)	(0.02)	(0.02)
TotalRating(t-2)	0.056***	0.087***	0.094***	0.093***
	(0.01)	(0.02)	(0.02)	(0.02)
AveRank	0.001	0.001	0.002	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
TopAlbum	0.249**	0.189***	0.302***	0.305***
	(0.08)	(0.05)	(0.07)	(0.09)
TopAlbum(t-1)	0.101	0.107	0.209*	0.214*
	(0.08)	(0.07)	(0.09)	(0.09)
PriorFests	-0.104***	-0.145***	-0.006	-0.006
	(0.01)	(0.02)	(0.02)	(0.02)
PriorFestRank	-0.002***	-0.003***	-0.006***	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)
LastToured	-0.118***	-0.028	-0.048*	-0.048*
	(0.01)	(0.02)	(0.02)	(0.02)
FirstTour	-0.080***	-0.225***	-0.224***	-0.224***
	(0.01)	(0.03)	(0.03)	(0.03)
TopTour	0.137	0.123	0.215*	0.213*
	(0.08)	(0.06)	(0.09)	(0.09)
TopTour(t-1)	-0.098**	-0.264*	-0.225**	-0.222**
	(0.03)	(0.10)	(0.08)	(0.08)
TourCosts		-0.535***	-0.556***	-0.558***
		(0.02)	(0.07)	(0.07)
FirstRating			-0.038	-0.081
			(0.06)	(0.10)
EverFest			-0.485***	-0.487***
			(0.04)	(0.04)
FirstRating*YearsToured				0.016
				(0.03)
Rating*TopAlbum				0.052
				(0.15)
Year Fixed Effects	Yes	Yes	Yes	Yes
Band Fixed Effects	Yes	Yes	Yes	Yes
Observations	5705	5705	5705	5705

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable, Fest, is an indicator for inclusion in any festival.
The marginal effect can be interpreted as the percentage change effect on
on hiring probability derived from a one unit change in the variable.

Table 2.11: Hiring Model with Total Quality Inclusions and Top Tour Indicators - Raw Results

	(1)	(2)	(3)	(4)
	Fest	Fest	Fest	Fest
TotalRating	0.321***	0.299***	0.283**	0.276**
	(0.0853)	(0.0862)	(0.0897)	(0.0912)
TotalRating(t-1)	0.635***	0.603***	0.565***	0.564***
	(0.0756)	(0.0763)	(0.0797)	(0.0800)
TotalRating(t-2)	0.389***	0.403***	0.377***	0.376***
	(0.0711)	(0.0723)	(0.0731)	(0.0732)
AveRank	0.00859	0.00612	0.00750	0.00755
	(0.00521)	(0.00530)	(0.00640)	(0.00641)
TopAlbum	1.256***	1.159**	1.310***	1.232**
	(0.347)	(0.354)	(0.364)	(0.442)
TopAlbum(t-1)	0.591	0.565	0.860*	0.883*
	(0.388)	(0.397)	(0.403)	(0.412)
PriorFests	-0.726***	-0.673***	-0.0238	-0.0240
	(0.0831)	(0.0844)	(0.0944)	(0.0943)
PriorFestRank	-0.0123***	-0.0131***	-0.0243***	-0.0243***
	(0.00236)	(0.00239)	(0.00259)	(0.00259)
LastToured	-0.824***	-0.130	-0.195*	-0.193*
	(0.0477)	(0.0800)	(0.0827)	(0.0828)
FirstTour	-0.668***	-0.950***	-0.987***	-0.984***
	(0.123)	(0.128)	(0.139)	(0.139)
TopTour	0.765*	0.661	0.887*	0.880*
	(0.390)	(0.403)	(0.419)	(0.418)
TopTour(t-1)	-0.920*	-1.100**	-1.021*	-0.999*
	(0.408)	(0.420)	(0.436)	(0.442)
TourCosts		-2.494***	-2.241***	-2.248***
		(0.250)	(0.253)	(0.253)
FirstRating			-0.156	-0.332
			(0.237)	(0.423)
EverFest			-2.622***	-2.622***
			(0.179)	(0.179)
FirstRating*YearsToured				0.0646
				(0.127)
TopAlbum*Rating				0.208
				(0.617)

Table 2.12: Prominence Models with an Indicator Measuring Quality

	(1) AveFestRank	(2) AveFestRank	(3) AveFestRank
Rating	-2.477	-1.999	-2.255
	(2.871)	(2.990)	(3.144)
Rating(t-1)	-8.215***	-9.010***	-8.986***
	(1.430)	(1.427)	(1.430)
Rating(t-2)	-6.185***	-6.606***	-6.588***
	(1.668)	(1.689)	(1.692)
AveRank	-0.0522	-0.0993	-0.0940
	(0.0920)	(0.0919)	(0.0935)
TopAlbum	-19.51***	-19.45***	-19.96***
	(2.807)	(2.780)	(3.563)
TopAlbum(t-1)	-19.53***	-19.33***	-19.22***
	(3.039)	(3.010)	(3.052)
PriorFests	-9.464***	-5.765***	-5.765***
	(0.658)	(0.768)	(0.769)
PriorFestRank	0.161***	0.140***	0.140***
	(0.0213)	(0.0213)	(0.0213)
LastToured	5.238***	5.144***	5.142***
	(0.539)	(0.533)	(0.533)
FirstTour	7.595***	6.948***	6.890***
	(1.744)	(1.727)	(1.741)
FirstRating		0.787	1.639
		(2.690)	(4.389)
EverFest		-13.06***	-13.07***
		(1.424)	(1.425)
FirstRating*YearsToured			-0.274
			(1.204)
Rating*TopAlbum			1.130
			(5.136)
Constant	78.56***	82.19***	82.18***
	(1.344)	(1.388)	(1.388)
Observations	3562	3562	3562
R^2	.32	.35	.35

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The dependent variable, AveFestRank, is the average "rank" of all the festivals a band is in.

Table 2.13: Prominence Models with Total Ratings Measuring Quality

	(1) AveFestRank	(2) AveFestRank	(3) AveFestRank
TotalRating	-0.531	-0.448	-0.463
	(0.736)	(0.738)	(0.759)
TotalRating(t-1)	-3.330***	-3.673***	-3.674***
	(0.557)	(0.553)	(0.555)
TotalRating(t-2)	-2.103**	-2.197**	-2.196**
	(0.679)	(0.684)	(0.685)
AveRank	-0.0859	-0.135*	-0.134*
	(0.0593)	(0.0658)	(0.0662)
TopAlbum	-19.93***	-19.88***	-19.90***
	(2.807)	(2.778)	(3.557)
TopAlbum(t-1)	-19.91***	-19.72***	-19.72***
	(3.030)	(3.000)	(3.047)
PriorFests	-9.411***	-5.658***	-5.655***
	(0.665)	(0.774)	(0.775)
PriorFestRank	0.158***	0.136***	0.137***
	(0.0214)	(0.0213)	(0.0213)
LastToured	5.322***	5.236***	5.236***
	(0.537)	(0.531)	(0.531)
FirstTour	7.939***	7.286***	7.239***
	(1.740)	(1.723)	(1.737)
FirstRating		1.635	2.407
		(2.570)	(4.295)
EverFest		-13.13***	-13.14***
		(1.424)	(1.425)
FirstRating*YearsToured			-0.272
			(1.207)
Rating*TopAlbum			-0.0112
			(5.023)
Constant	78.41***	82.02***	82.02***
	(1.342)	(1.384)	(1.385)
Observations	3562	3562	3562
R^2	.38	.38	.38

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable, AveFestRank, is the average “rank” of all the festivals a band is in.

album of unanimous quality included in each of the lists, the combined effects of all three years of ratings measures will not match the single year rank increase of almost 20 places that comes from having a top album. The impact of a top album is almost as large in the lagged year as well, leading to the conclusion that festivals are hiring bands that do well in quality measures for the effect on reputation in ensuing periods, and hiring bands with well selling albums for their immediate impact on demand.

The effects of some simple band characteristics on determining prominence have reversed from their effect on probability of hiring. $EverFest$ has a substantially negative impact on being hired in a given year. However, once hired the experience of having played before means a more prominent position in the lineup by slightly more than thirteen places in both models. Festivals are choosing their known bands carefully, but they are being hired in order to be used prominently. This is further reinforced with $PriorFests$, where there is an effect of between 5.6 and 9.4 in improved rank in each model for each prior festival played. Confirming the importance of experience is that unknown bands on their first tour are likely to be lower in prominence by seven to ten places in the lineup. Additionally, for each year elapsed since a band has toured there is a drop in rank of close to 5.5. Experience was shown to have an initial negative impact on the hiring in earlier models, but is clearly important to how prominently a band is placed, and therefore to their expected effect on demand for the festival.

2.6.5 Prominence within a Festival with Touring Indicators

Prominence models with the reduced sample of years that include an indicator for the top 100 tours are available in Tables 2.14 and 2.15, where it is clear that accounting for high revenue tours does not greatly affect the quality measure coefficients. What does change considerably is the estimate on having a top album and its lag. Much of the prominence effect of having a top album is eliminated as another demand variable is included. In fact, although $TopTour$ and its lag were not important in hiring probability, they are now the single most important effect on rank within a festival with an increase in rank of 20 in the first year and 17 in the second. Festivals are cautious about hiring bands with commercial success, but place those they do in the most prominent positions. Young bands of quality are used to fill smaller roles that will enhance the repuation of the festival.

Table 2.14: Prominence Models with Simple Indicator Measuring Quality and Touring Indicators

	(1) AveFestRank	(2) AveFestRank	(3) AveFestRank
Rating	-1.099	-1.195	-0.903
	(3.556)	(3.836)	(4.037)
Rating(t-1)	-7.597***	-7.862***	-7.894***
	(1.759)	(1.780)	(1.783)
Rating(t-2)	-7.885***	-7.846***	-7.869***
	(2.109)	(2.172)	(2.175)
AveRank	-0.0529	-0.0627	-0.0688
	(0.115)	(0.114)	(0.117)
TopAlbum	-13.75***	-13.67***	-12.95**
	(3.771)	(3.766)	(4.886)
TopAlbum(t-1)	-8.978*	-8.696*	-8.865*
	(4.393)	(4.387)	(4.480)
PriorFests	-8.577***	-6.495***	-6.495***
	(0.961)	(1.211)	(1.213)
PriorFestRank	0.210***	0.188***	0.188***
	(0.0341)	(0.0349)	(0.0351)
LastToured	7.127***	7.052***	7.062***
	(0.573)	(0.574)	(0.574)
FirstTour	10.43***	10.08***	10.20***
	(1.944)	(1.944)	(1.963)
TopTour	-19.83***	-19.68***	-19.64***
	(4.582)	(4.586)	(4.592)
TopTour(t-1)	-16.81**	-17.74**	-17.88**
	(5.696)	(5.705)	(5.739)
FirstRating		0.495	-1.413
		(3.307)	(5.714)
EverFest		-6.045**	-6.072**
		(2.153)	(2.156)
FirstRating*YearsToured			0.683
			(1.719)
Rating*TopAlbum			-1.524
			(7.037)
Constant	63.94***	65.01***	64.99***
	(1.412)	(1.461)	(1.463)
Observations	1656	1656	1656
R^2	.367	.37	.38

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable, AveFestRank, is the average "rank" of all the festivals a band is in.

Table 2.15: Prominence Models with Total Ratings Measuring Quality and Touring Indicators

	(1) AveFestRank	(2) AveFestRank	(3) AveFestRank
TotalRating	-0.851	-0.861	-0.800
	(0.892)	(0.908)	(0.935)
TotalRating(t-1)	-3.364***	-3.432***	-3.440***
	(0.673)	(0.676)	(0.677)
TotalRating(t-2)	-2.856***	-2.811***	-2.818***
	(0.789)	(0.804)	(0.805)
AveRank	-0.0393	-0.0624	-0.0635
	(0.0721)	(0.0794)	(0.0796)
TopAlbum	-13.69***	-13.68***	-12.76**
	(3.758)	(3.752)	(4.875)
TopAlbum(t-1)	-8.084	-7.785	-8.029
	(4.406)	(4.400)	(4.496)
PriorFests	-8.405***	-6.315***	-6.316***
	(0.974)	(1.223)	(1.225)
PriorFestRank	0.207***	0.186***	0.186***
	(0.0342)	(0.0350)	(0.0352)
LastToured	7.211***	7.146***	7.156***
	(0.568)	(0.568)	(0.569)
FirstTour	10.77***	10.42***	10.51***
	(1.932)	(1.933)	(1.952)
TopTour	-20.27***	-20.08***	-20.01***
	(4.572)	(4.570)	(4.580)
TopTour(t-1)	-16.17**	-17.14**	-17.34**
	(5.689)	(5.692)	(5.734)
FirstRating		1.336	0.121
		(3.088)	(5.548)
EverFest		-6.005**	-6.030**
		(2.154)	(2.157)
FirstRating*YearsToured			0.448
			(1.718)
Rating*TopAlbum			-1.958
			(6.878)
Constant	63.62***	64.66***	64.65***
	(1.390)	(1.437)	(1.439)
Observations	1656	1656	1656
R^2	.37	.38	.38

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable, AveFestRank, is the average “rank” of all the festivals a band is in.

Band experience still has an important effect on prominence under this model, however, the coefficient on $EverFest$ is now less important than it was in previous models. The number of prior festivals is now also lower, indicating that experience alone is not sufficient for significant promotion; quality and demand measures are also very important. An unknown band can still expect to be ranked lower. A band's first tour now means an even less prime position in the festival, correlated with a decrease in rank of 10.5 compared to about seven in the earlier models. Additionally, each year since a band last toured has a stronger negative effect on average rank of seven spots compared to about five previously.

Adding touring as a robustness check is more important in the prominence model than it was in hiring. The quality measures are largely unchanged, but much of the effect from having a top album is now transferred to operating a top tour. Additionally, the experience of bands is shown to be important, but not as meaningful without quality and demand. The variables indicating a band without much touring or festival experience are absolutely correlated with increased promotion, showing that festivals are likely to exploit the expertise of festivals operated before them, and prominently place bands which had been highly ranked before.

2.6.6 Prominence Model with Ranking as a Percentage of Festival Size

As a final prominence robustness test, I consider the possibility that the size of the festivals affects ranking. The general expansion of each of the festivals from year to year causes more slots to open up and increases the average ranking of a festival, potentially biasing the raw rank results. In Tables 2.16 and 2.17 the dependent variable is the rank of bands playing a festival as a percentage of the total spots available in the festivals they play, where again a lower percentage indicates a higher prominence. The coefficients represent a percentage change in rankings given the available slots in a year. The results reinforce the ranking models. Every sign remains the same as in the previous models and the coefficient on the percentage changes are slightly stronger than the raw results evaluated at their average. The varying number of performers in festivals does not bias the results.

Table 2.16: Percentage Prominence Models with Simple Ratings Measuring Quality

	(1) PerRank	(2) PerRank	(3) PerRank
Rating	-0.0375	-0.0335	-0.0395
	(0.0237)	(0.0248)	(0.0261)
Rating(t-1)	-0.0828***	-0.0872***	-0.0867***
	(0.0122)	(0.0122)	(0.0123)
Rating(t-2)	-0.0611***	-0.0628***	-0.0623***
	(0.0144)	(0.0146)	(0.0147)
AveRank	-0.000239	-0.000592	-0.000474
	(0.000757)	(0.000759)	(0.000772)
TopAlbum	-0.168***	-0.168***	-0.180***
	(0.0230)	(0.0228)	(0.0293)
TopAlbum(t-1)	-0.130***	-0.128***	-0.125***
	(0.0269)	(0.0268)	(0.0273)
PriorFests	-0.0754***	-0.0500***	-0.0500***
	(0.00594)	(0.00705)	(0.00705)
PriorFestRank	0.00136***	0.00119***	0.00119***
	(0.000196)	(0.000197)	(0.000197)
LastToured	0.0540***	0.0536***	0.0535***
	(0.00448)	(0.00445)	(0.00446)
FirstTour	0.0740***	0.0696***	0.0683***
	(0.0144)	(0.0144)	(0.0145)
FirstRating		0.00796	0.0258
		(0.0222)	(0.0362)
EverFest		-0.0852***	-0.0853***
		(0.0129)	(0.0129)
FirstRating*YearsToured			-0.00569
			(0.00997)
Rating*TopAlbum			0.0264
			(0.0422)
Constant	0.536***	0.556***	0.557***
	(0.0114)	(0.0117)	(0.0117)
Observations	3049	3049	3049
R^2	.28	.30	.31

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable, PerRank, is the average “rank” as a percentage of total festival slots available.

Table 2.17: Percentage Prominence Models with Total Ratings Measuring Quality

	(1)	(2)	(3)
	PerRank	PerRank	PerRank
TotalRating	-0.0127*	-0.0117	-0.0127*
	(0.00608)	(0.00613)	(0.00630)
TotalRating(t-1)	-0.0349***	-0.0368***	-0.0367***
	(0.00487)	(0.00486)	(0.00487)
TotalRating(t-2)	-0.0205***	-0.0207***	-0.0205***
	(0.00583)	(0.00589)	(0.00590)
AveRank	-0.000628	-0.00101	-0.000976
	(0.000486)	(0.000540)	(0.000544)
TopAlbum	-0.169***	-0.169***	-0.177***
	(0.0230)	(0.0228)	(0.0292)
TopAlbum(t-1)	-0.136***	-0.134***	-0.131***
	(0.0268)	(0.0267)	(0.0272)
PriorFests	-0.0752***	-0.0493***	-0.0493***
	(0.00600)	(0.00711)	(0.00711)
PriorFestRank	0.00134***	0.00116***	0.00117***
	(0.000197)	(0.000198)	(0.000198)
LastToured	0.0547***	0.0543***	0.0543***
	(0.00447)	(0.00444)	(0.00444)
FirstTour	0.0770***	0.0725***	0.0711***
	(0.0144)	(0.0143)	(0.0144)
FirstRating		0.0149	0.0343
		(0.0212)	(0.0354)
EverFest		-0.0853***	-0.0855***
		(0.0128)	(0.0129)
FirstRating*YearsToured			-0.00670
			(0.00999)
Rating*TopAlbum			0.0178
			(0.0413)
Constant	0.534***	0.554***	0.554***
	(0.0114)	(0.0117)	(0.0117)
Observations	3049	3049	3049
R^2	.28	.30	.31

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The dependent variable, PerRank, is the average "rank" as a percentage of total festival slots available.

2.7 Conclusion

Music Festivals must carefully consider which bands to hire for their annual production. The period studied coincides with a period in which bands began to generate a larger percentage of their income from touring, corresponding with easier consumer access to new music, increasing demand for concerts, and increasing concert prices (Mortimer et al., 2012). The festival cannot then simply depend on hiring the most popular group of each genre and creating the appropriate demand. The difficulty of the task can be seen by the many large music festivals that have shut down for lack of profitability.[18] Successful operations find the appropriate mix of known and unknown bands that create enough current demand and enhance their reputation sufficiently at costs low enough to remain profitable from year to year. In order to maintain the optimal lineup these festivals must be able to minimize the costs of their headliners that will drive much of their demand, as well as recognize quality of unknown bands ahead of the wider base of music customers.

Hiring decisions are then split into two primary considerations. First, the festival must hire unknown bands which their consumers will enjoy but are not yet exposed to. These bands benefit a festival because they can enhance reputation and customer experience at a lower fee. This is not to say that newly formed bands on their first tour are likely to be hired, the festival needs the opportunity to evaluate their potential hire. However, bands without festival experience are more often hired. The most important measurable characteristic of these bands is their quality, specifically inclusion in quality measures. Because they very rarely have top albums or tours, inclusion in these measures is the best chance for being hired by a festival.

After the initial festival appearance some bands are more likely to be rehired than others. Among bands that are already known to consumers, experience and proven demand are important. For at least a single year, bands with top tours and top albums are more likely to be hired. Known bands are also more likely to be hired if they have considerable festival experience. Inclusion in quality measures significantly improves the probability of hiring for these bands as well, where widespread recognition of quality can nearly guarantee festival participation in ensuing years. The lasting impact of recognized quality shows it to be more of a reputation enhancing effect for the festival than the transitory popularity associated with a top album or tour.

[18]For examples see Vegoose, Langerado, Monolith, and All Points West music festivals.

Once hired the important characteristics for prominence within a festival change from the hiring model, indicating that the festival is compromising on hiring decisions to produce the festival based on more characteristics than simply immediate demand considerations. The large music festival must make their hiring decisions based on the horizontally differentiated demand of consumers, the fees paid to bands of varying levels of quality and popularity, and with considerations of how these decisions will affect their reputation for the future. Promotional decisions are simply based on expected demand of the bands they hired and reaching the critical demand necessary for that year's production. In promotion, quality becomes less important and the demand characteristics of top albums and tours become more significant. The different criteria for hiring and promtion can be explained by the increased costs of hiring commercially popular bands. The prominence models show these characteristics are certainly important to festivals, but the increased fees necessary to hire them mean they must substitute some quality bands with low popularity for the more established bands that could create the largest immediate demand in a long term strategy.

The hiring practices of music festivals also illustrate the ability of a firm to bundle various levels of quality in order to create a profitable venture. Results show that if the firm is able to identify characteristics of their inputs that will create future demand for the consumer but have not yet been recognized for their full value, then they may be employed for less than their quality level would warrant. The bundling of these inputs with known and unknown levels of quality then creates the demand that a music festival must have in order to make their production profitable.

This explanation provides likely insight into the music festival, but further research may extend the idea to other industries and operations. Examples would include industries where quality and cost are related, but may not be perfectly correlated. The most obvious industries are professional sports, where teams may hire players without full knowledge of the level of quality based on potential customer utility and streaming online video services. Other entertainment industries such as movie production could also base their decisions on this model when hiring actors and establishing effects budgets. These are several examples of possible industries which could be explained through similar models, but this list is by no means extensive.

Table 2.18: Variable List

Variable	Description
ACL	Austin City Limits Music Festival.
Bonnaroo	Bonnaroo Music Festival.
Coach	Coachella Music Festival.
Lol	Lollapalooza Music Festival.
Glast	Glastonbury Music Festival.
Bestever	Indicator for a music rating from Bestever.com.
Mojo	Indicator for a music rating from *Mojo*.
Pitchfork	Indicator for a music rating from Pitchfork.com.
Spin	Indicator for a music rating from *Spin*.
NME	Indicator for a music rating from *NME*.
Metacritic	Indicator for a music rating from Metacritic.com.
Fest	Indicator for a band playing in any music festival in a year.
Rating	Indicator for a band receiving at least one quality rating in a year.
TotalRating	The total number of quality measures a band is included in in a year.
AveRank	Average rank for quality indexes a band is included in in a year.
TopAlbum	Indicator for a band with a top 200 gross revenue album in a year.
TopTour	Indicator for a band with a top 100 gross revenue tour in a year.
PriorFests	The number of festivals a band has particpated in in its past.
LastToured	How long ago a band last toured.
FirstTour	Indicator for a band producing its first tour in the sample.
TourCosts	Indicator for a band not touring outside of a festival in a year.
FirstRating	Indicator for a first quality rating by a band.
EverFest	Indicator if a band has ever played a festival before.
PriorFestRank	The average previous ranking for a band if they played a festival within the last two years.

CHAPTER III

Market Structure and Media Diversity

3.1 Introduction

Information on news and current affairs can raise political awareness and promote a range of ideas. Under the assumption that unregulated media markets supply too little variety, many societies have charged regulators with ensuring there are sufficient opportunities for different, new, and independent viewpoints (which we shall refer to as "diversity" below), and that media respond to the interests of their local communities ("localism"). In the U.S., the Federal Communications Commission (FCC) has traditionally limited the amount of common- and cross-ownership of newspapers, radio, and television (TV) stations. Recently, the FCC relaxed ownership rules and refocused their attention on market forces; for example, consumer preferences and new media, such as satellite, the Internet, and Smartphone, in order to achieve their diversity and localism goals. Given the increase in choices through new media, supporters of greater ownership concentration argue that traditional media should be free to consolidate and use the efficiencies to provide more diverse and local news programming. Opponents question whether such efficiencies are achievable, and argue that large, consolidated media corporations are not flexible enough to serve the interests of local and minority communities.

Evaluation of these arguments requires, among other things, measurement of the expected societal benefits that arise from increased media diversity and localism, and how these benefits change with regulatory interventions that shape media market structure. In this paper, we estimate consumer preferences for their local news and current affairs ("news service") described by the offerings from newspapers, radio, TV, the Internet, and Smartphone. News service characteristics are: diversity of opinion in the reporting of information, coverage of multiculturalism issues, amount of information on community news and events, and amount of space or time devoted to advertising. We use our demand estimates to calculate the impact on consumer welfare from a change in media market structure that reduces the number of independent TV stations in the market.[1] Specifically, we employ the willingness-to-pay (WTP) construct to measure the expected welfare effects between the news service supplied to the consumer before the change in market structure and the service supplied after the change. We focus on broadcast TV stations because they are the main source of news for most households and because the FCC has direct oversight of their ownership structure.[2] By relating consumer valuations of news service to a measure of TV market structure, it is possible to indirectly assess the extent to which ownership rules address the policy goals of diversity and localism.

We estimate our demand model with data obtained from a nationwide survey of U.S. households during March, 2011. Results show that diversity of opinion, community news, and advertising are important characteristics of local news services. The representative consumer is willing to pay from $21 to $25 per month for an increase in diversity of opinion (and approximately the same for community news) from a low to a medium level (defined in Table 3.1), but only an additional $6 to $7 to move to a high level of diversity of opinion (or community news). The representative consumer also values an improvement in information that reflects the interests of women and minorities from low to medium ($7). Many consumers have a distaste for advertising, which likely reflects their consumption of general, all-purpose advertising from traditional media such as radio and TV. The representative consumer is willing to pay about $5 to avoid a movement from a low to a medium level of advertising, but the much higher amount of $17 to avoid a movement from a medium to a high level.

Using FCC data on media market structure, we present evidence that indicates the amount of diversity, localism, and advertising in the news services supplied to consumers is lower in markets with one fewer independent TV station. As a result, the average "small market" (i.e., five or fewer TV stations) consumer loses $0.83 per month, whereas the average "large market" (i.e., 20 or more

[1] The number of independent (parent company) TV stations is determined by counting all stations within a market. For every station with a common parent, we then count only the first of those stations along with the remaining stations with no common parent. See Section 3.4 for a detailed description.

[2] At 2010, 58 percent of the public turned on the TV for news, 44 percent used the Internet or their cellular telephone, 34 percent turned on the radio, and 31 percent read the newspaper (Pew Research Center; 2010).

Table 3.1: Summary of News Service Characteristics

Characteristic	Level
COST (p)	The total of monthly subscriptions to all of the household's media sources, plus any contributions to public radio or public TV stations (ranging from \$0 to \$250 per month).
DIVERSITY OF OPINION (x_1)	The extent to which the information on news and current affairs in the household's overall media environment reflects different viewpoints. Low: only one viewpoint. Medium: a few different viewpoints. High: many different viewpoints.
COMMUNITY NEWS (x_2)	The amount of information on community news and events in the household's overall media environment. Low: very little or no information on community news and events. Medium: some information on community news and events. High: much information on community news and events.
MULTICULTURALISM (x_3)	The amount of information on news and current affairs in the household's overall media environment that reflects the interests of women and minorities. Low: very little or no information reflecting the interests of both. Medium: some information reflecting the interests of women and minorities. High: much information reflecting the interests of women and minorities.
ADVERSTISING (x_4)	The amount of space and/or time devoted to advertising in the household's overall media environment. Low: barely noticeable. Medium: noticeable but not annoying. High: annoying.

The upper limit of \$250 per month for COST is the total cost for a media environment with a seven-day subscription to a premium newspaper, such as the New York Times or San Francisco Chronicle (\$25), a "All of XM" subscription to satellite radio (\$20), a premier subscription to cable or satellite television (\$110), a subscription to very-fast Internet service (\$45), an unlimited data subscription for a Smartphone (\$30), and \$10 monthly memberships to both NPR and PBS. Detailed descriptions of the characteristics as they appeared in the survey questionnaire are available in Savage and Waldman (2011).

TV stations) consumer loses \$0.37 per month. These losses are equivalent to \$45 million annually for all small-market households in the U.S. and \$13 million for large-market households. If the change in market structure occurs in all markets, aggregate losses nationwide would be about \$681 million.

Other studies have measured the relationship between information on news and current affairs and market structure. However, these studies measure supply from just one of the media sources that comprise the consumer's news service; for example, Milyo (2007), Gentzkow (2007) and Gentzkow and Shapiro (2013) for newspapers, and Siegelman and Waldfogel (2001) and Crawford (2007) for radio and TV. Our research is also related to studies that quantify the relationship between quality and market structure for different industries. For example, Mazzeo (2003) shows that average flight delays are longer in more concentrated airline markets. Goolsbee and Petrin (2004) estimate that cable TV channel capacity, number of over-the-air channels and number of premium movie channels increased in response to satellite entry. Matsa (2011b) finds that supermarkets facing more intense competition have more products available on their shelves, while Olivares and Cachon (2009) show that the inventories of General Motors dealerships increases with the number of competitors. In contrast, Domberger (1989) find no correlation between the threat of new entry and customer's satisfaction with their attorney used for home purchases.[3] Because we measure the change in market structure by reducing the number of independent TV stations, our paper is also related to structural models of differentiated oligopoly that predict the price effects from a simulated merger; for example, Nevo (2000) for breakfast cereals, Pinkse and Slade (2004) for U.K. brewing, and Ivaldi and Verboven (2005) for car manufacturing.

Relative to these literatures our study makes several contributions. First, we offer new evidence from media markets by examining the potential welfare effects from a news service bundled from newspapers, radio, TV, the Internet, and Smartphone. Second, the prediction of non-price effects appears to be novel in the simulated merger literature. Finally, by looking at a vector of non-price effects we are able to document a new and interesting tradeoff between the diversity and localism characteristics of news service, and advertising. That is, the amount of diversity and localism

[3]Some papers exploit a law or regulatory change to document the effect of a change in market structure on the supply of media and telecommunications services. Berry and Waldfogel (2001) show that, following the Telecommunications Act of 1996 ("Act"), consolidation reduced radio station entry and increased product variety. Economides et al. (2008) show that following the Act, households benefited more from the new plan and quality differences offered by entrants into local telephone markets than from price decreases.

declines following a decrease in the number of independent TV stations, which is a cost to the typical consumer, but so too does the amount of advertising, which is a benefit to the typical consumer. This finding should be interesting to antitrust officials and policy makers because it highlights an additional potential benefit for consideration during the analysis of a media market merger. It also provides a new angle from which to assess the efficacy of media ownership rules.

The remainder of this paper is organized as follows. Section 2 outlines the demand model. Data are described in Section 3. Section 4 presents demand estimates and calculates consumer valuations for the diversity, localism and advertising characteristics of a news service. Section 5 uses the consumer valuations from Section 4 to conduct a simple policy experiment that estimates the impact on consumer welfare from a change in market structure. Section 6 concludes.

3.2 Demand Model

We examine the relationship between market structure and media diversity by asking two questions: what are the expected societal benefits that arise from increased media diversity and localism, and how do these benefits change with regulatory interventions that shape media market structure? The first question is answered by estimating a model of the demand for news service with discrete choice data. The estimated preferences from the representative household's utility function are then used to calculate consumer's WTP for each of the non-price characteristics of their news service. The second question is answered with a simple policy experiment that uses our demand estimates to calculate the impact on consumer welfare from a change in market structure that reduces the number of independent TV voices by one. The demand model is described below.

3.2.1 Household Choice for News Services

There are several problems when estimating demand for news service with market data. First, households consume a bundle of entertainment and news services from the offerings from newspapers, radio, TV, the Internet, and Smartphone, but data on these bundles, their non-price characteristics, and prices are not readily available. Second, even when available, these data are unlikely to exhibit sufficient variation for the precise estimation of demand parameters. For example, the levels for the diversity and localism characteristics are often highly, positively correlated.

Third, news services are a mixture of private and public goods and many households, e.g., those who bundle broadcast radio and TV stations, make no direct payment for consumption. Because detailed data on the amount of advertising within household bundles are not available, it is not possible to accurately measure the full cost of news services.

We overcome these problems by using an indirect valuation method, similar to that used in the environmental economics and transportation choice literature, that employs market and experimental data. The market data is the news service households currently consume. The experimental data is a set of constructed news services. We design a choice set that manipulates the levels of the characteristics of the constructed news services to obtain the optimal variation in the data needed to estimate the demand parameters precisely. Respondents choose between a pair of constructed news services, and then between that choice and their actual news service at home. Because our design exogenously determines the levels of the characteristics of each news service, and randomly assigns the levels across respondents, we limit measurement and collinearity problems. Furthermore, by asking respondents to complete eight such choice occasions, we increase parameter estimation precision, and reduce sampling costs by obtaining more information on preferences for each respondent.

The conditional indirect utility function for household n from news service alternative j on choice occasion t is assumed to be:

$$U^*_{njt} = \alpha p_{njt} + \sum_{g=2,3} \alpha_g p_{njt} y_{gn} + \beta_n' x_{njt} + \xi_{njt} + \varepsilon_{njt} \tag{3.1}$$

where α is the marginal utility of price, p is price, β_n is a vector of consumer-specific marginal utility coefficients, x_{njt} is a vector of observed non-price characteristics of entertainment and news service, ξ_{njt} is the utility from unobserved entertainment services and from other dimensions of news not included in x_{njt}, and ε_{njt} is an unobserved random error term that is independently and identically distributed extreme value. The effect on utility from price is specified to vary by three income groups, with the dummy variable y_{gn} indicating which household n is in income group g. The marginal utility of price for the low income group (i.e., household income of $25,000 or less) is α and the marginal utility of price for a household in income group g is $\alpha + \alpha_g$. The income dummy variables are y_{2n} (or MED_INCOME), which equals one when household income is greater than $25,000 and less than $50,000 and zero otherwise, and y_{3n} (or HIGH_INCOME), which equals one when household income is greater than \$50,000 and zero otherwise.

The density of the distribution for β_n is $f(\beta_n|\theta)$ with θ measuring the mean and covariance parameters of β_n. Assuming $\beta_n = b + \eta_n$, utility can be rewritten as:

$$U^*_{njt} = \alpha p_{njt} + \sum_{g=2,3} \alpha_g p_{njt} y_{gn} + b' x_{njt} + \eta_n x_{njt} + \xi_{njt} + \varepsilon_{njt} \tag{3.2}$$

where b is the population mean marginal utility from non-price characteristics and η_n is the individual consumer's deviation from this mean. Given ε is distributed extreme value, and assuming an appropriate distribution for β_n, mixed logit estimation of equation 2 is possible by simulated maximum likelihood (Revelt and Train, 1998; Brownstone and Train, 1998). In our choice scenario described in Section 3, the consumer chooses between three alternatives in each choice occasion that differ in their levels of x_{njt} and p_{njt} only. By holding all other dimensions of entertainment and news services in equation 2 constant so that $\xi_{njt} = \xi_n$, the model controls for potential correlation between price and quality that is not observed by the researcher.

Table 3.1 describes the levels of the characteristics that comprise the elements of the vector x_{njt}, and p_{njt}. DIVERSITY OF OPINION (x_1) is the extent to which the information on news and current affairs in the household's news service reflects different viewpoints. MULTICULTURALISM (x_2) is the amount of information on news and current affairs that reflects the interests of women and minorities. COMMUNITY NEWS (x_3) is the amount of information on community news and events, and ADVERTISING (x_4) is the amount of space and/or time devoted to. COST (p) is the dollar amount the household pays per month for their news service. That is, the total of monthly subscriptions to all media sources, plus any contributions to public radio or public TV stations.

3.2.2 Willingness-to-Pay for News Service Characteristics

Since they do not have an understandable metric, it is convenient to convert the estimated marginal utilities for changes in x_{njt} into WTP. For example, the WTP for a one unit increase in diversity of opinion (WTP_d) is defined as how much more the news service would have to be priced to make the consumer just indifferent between the old (cheaper but with only one viewpoint) service and the new (more expensive but with a few different viewpoints) service. Mean WTP for diversity of opinion, for each income group, can be calculated from our estimates of utility as:

$$WTP_d = \frac{-b_1}{\alpha + \sum\limits_{g=2,3} \alpha_g y_{gn}} \tag{3.3}$$

where b_1 is the mean marginal utility of DIVERSITY OF OPINION.[4] This approach to estimating consumer valuations is used for the three other non-price characteristics of local news service.[5]

Because equation 3 is a function of random variables, WTP is also a random variable with appropriate standard errors and confidence intervals. We calculate standard errors for WTP using a bootstrapping method. First, marginal utility values for individual household n are drawn from the multivariate normal distribution implied by the mean (b) and covariance (η_n) parameters estimated from equation 2. The marginal utilities are then substituted into equation 3 to calculate household n's WTP and the mean WTP for all households. This simulation is repeated 1,000 times to derive the sampling distribution for WTP for each income group g. Standard errors for WTP, by income group g, are estimated from this sampling distribution.

3.3 Data

3.3.1 Survey Design

The WTP for local media environment features are estimated with data from an online survey questionnaire employing repeated discrete-choice experiments. The questionnaire begins with a cognitive buildup section that describes the respondent's local news service in terms of the offerings from newspapers, radio, TV, the Internet, and Smartphone. Respondents are asked questions about their media sources, how much information they consume from each source, the cost of their media sources, and the levels of the four different characteristics of their news service described in Table 3.1.[6]

The cognitive buildup section is followed by the choice scenarios. Information from the cognitive buildup questions is used to summarize each respondent's actual entertainment and news service at

[4] The discrete-choice model actually estimates $\frac{\alpha}{\sigma}$ and $\frac{b1}{\sigma}$, where σ is the scale parameter. The WTP calculation is not affected by the presence of the scale parameter because $-\frac{b_1}{\sigma}/\frac{\alpha}{\sigma} = \frac{-b_1}{\alpha}$.

[5] WTP may also vary with observable demographics.

[6] Respondents were asked to consider what is available in their local media environment, rather than what they usually view or listen to. This represents a statement about the amount and quality of information programming being produced by media sources for their consumption.

home with respect to their media sources, the levels of the non-price characteristics of their service, DIVERSITY OF OPINION, MULTICULTURALISM, COMMUNITY NEWS and ADVERTISING, and their COST. A table summarizing the sources and characteristics of the respondent's actual media environment at home is presented to the respondent before the choice scenario. The respondent is then instructed to choose in eight choice occasions. In each occasion, the choice is between their actual news service at home and two constructed new service alternatives, labeled A and B, that differ by their levels of DIVERSITY OF OPINION, MULTICULTURALISM, COMMUNITY NEWS, ADVERTISING and COST.

We used market data from newspapers, radio and TV stations, Internet and mobile telephone service providers, a pilot study, and three focus groups to test and refine our descriptions of the characteristics for news service alternatives. Measures developed by Huber and Zwerina (1996) were used to generate an efficient non-linear optimal design for the levels of the constructed news characteristics. A fractional factorial design created 72 paired descriptions of A and B news services that were grouped into nine sets of eight choice questions. The nine choice sets were rebalanced to ensure that each household faced a range of costs that realistically portrayed the prices for media sources in their local market. For example, a respondent who indicated that they pay nothing for their news source was exposed to a range of costs that included zero dollars per month.[7] The nine choice sets, along with the order of the eight A-B pair choice alternatives within each choice set, were randomly assigned to respondents.

3.3.2 Survey administration

Knowledge Networks Inc. (KN) administered the online survey. Panel members are recruited through national random samples, almost entirely by postal mail. For incentive, they are rewarded with points for participating in surveys, which can be converted to cash or other rewards. During the week of March 7, 2011, KN randomly contacted a gross sample of 8,621 panel members to inform them about the survey. The survey was fielded from March 11 to March 21. A total of 5,548 respondents from all 50 states and the District of Columbia completed survey questionnaires. Because of incomplete survey responses, we trimmed the sample by 417 respondents. The median

[7]Upon completion of their cognitive buildup questions, an online algorithm calculated each individual's total cost of their local entertainment and news service and assigned the appropriate cost range for their choice occasions.

completion time for our sample of 5,131 respondents with complete information was about 17 minutes.

Table 3.2 presents a selection of demographics for the U.S. population, for all KN's panel members, and for panel members who were invited to participate in this survey (United States Census Bureau; Knowledge Networks, Inc.). The demographics for all KN panel members are similar to those reported by the Census Bureau. Inspection of column four and column five of Table 3.2 also show that, apart from race and employment status, the demographics for the gross sample of panel members invited to participate in this study and the final sample of respondents who completed questionnaires are also similar to those reported by the Census Bureau. However, estimates from a probit model that compares respondent's characteristics between the gross sample and the final sample also indicate potential differences in age, gender, education, and Internet access between our final sample and the population. We remedy this possible source of bias in our demand results by estimating with weighted maximum likelihood.

3.3.3 Media Sources and News Service

Table 3.3 presents summary statistics for respondent's media sources. Columns two and three show that about 95 percent of sample respondents watch TV, 81 percent listen to the radio, and 81 percent use the Internet. About 45 percent of respondents read a print newspaper or online newspaper regularly, and 24 percent of sample respondents own a Smartphone.[8] On average, to get information on news and current affairs, TV viewers spend about 1.9 hours on a typical day watching TV, radio listeners spend 1.4 hours listening to the radio, and Internet users spend one hour online (e.g., MSN, Yahoo, radio and TV station web sites, journalists' blogs). Newspaper readers spend about one hour on a typical day reading the newspaper, while Smartphone owners use their phone to go online for 0.6 hours to get information on news and current affairs. The most popular media source combinations are radio, TV and the Internet, about 30 percent of sample respondents, and newspaper, radio, TV and the Internet, about 26 percent of sample respondents.

Summary statistics for news service characteristics are presented in Table 3.4. These data indicate that, on average, the levels of the DIVERISTY OF OPINION, MULTICULTURALISM,

[8]Data from the Neilson Company and the U.S. Census Bureau indicate that about 93 percent of persons watch TV, 82 percent listen to the radio, and 77 percent use the Internet. About 67 percent of respondents read a newspaper regularly, and 25 percent of sample respondents own a Smartphone.

Table 3.2: Demographic Distributions

	Census	KN panel	KN sample			
			Gross sample (Invited)	Full sample (Completed)	Final sample (Completed)	Omitted (Completed)
Northeast	18.4	18.5	18	18.5	18.3	21.8
Midwest	21.8	22.1	23.4	24.7	24.9	21.3
South	36.5	35.9	35.6	34.2	34.4	31.4
West	23.2	23.5	22.9	22.6	22.4	25.4
18-24 years	12.6	10.7	10.7	8.6	7.6	21.8
25-34 years	17.8	17.4	15	12.7	11.3	29.7
35-44 years	17.8	18.9	16.6	16.1	15.8	20.1
45-54 years	19.5	18.5	20.1	20.3	20.9	13.2
55-64 years	15.5	18.5	20.3	22.2	23.3	9.1
65 years or over	16.8	16	17.3	20.1	21.2	6
Non-white	18.9	20.9	30.3	26	25.4	33.3
White	81.1	79.1	69.7	74	74.6	66.7
Female	51.7	52.6	53	50.8	51.1	47.5
Male	48.3	47.4	47	49.2	49.9	52.5
Married	55.1	52.5	53.5	55.1	55.8	46.3
Not married	44.9	47.5	46.5	44.9	44.2	53.7
< High school	13.8	12.9	10.8	9.6	9.5	10.8
High school	30.7	29.6	29	30.2	30	32.6
Some college	28.2	29.1	31.3	29.8	30	27.6
Bachelors or higher	27.4	28.3	28.9	30.4	30.5	29
< $10,000	6.6	7	7.1	6.3	6.3	6.7
$10,000-$24,999	16.8	16.1	15.1	14.4	14.3	14.6
$25,000-$49,999	26.2	26.1	24.3	24.8	24.6	27.1
$50,000-$74,999	19.5	20.3	18.3	18.8	19.1	15.9
> $75,000-	30.8	30.4	35.2	35.7	35.7	35.7
In labor force	66.1	67.3	56.8	55.2	54.7	60.7
Not in labor force	33.9	32.7	43.2	44.8	45.3	39.3
Internet access	64	66	73	81.2	80.6	88.2
Observations	n.a.	n.a.	8,621	5,548	5,131	417

NOTES. Census data are from December, 2009. KN panel data are from January, 2010. Remaining data are from March, 2011.

Table 3.3: Summary Statistics for Media Sources

Media source	Obs.	Sample share (%)	Mean	s.d.	Min	Max
Newspaper	2,342	45.6	1.015	1.766	0	24
Radio	4,154	81.2	1.423	1.873	0	24
Satellite radio	558	10.9	1.522	2.221	0	24
Television	4,856	94.6	1.953	2.172	0	24
Cable television	2,736	53.4	1.976	2.21	0	24
Satellite television	1,381	27	2.071	2.197	0	24
Own Internet	4,135	80.6	1.074	1.659	0	24
Smartphone	1,270	24.8	0.58	1.344	0	24

NOTES. Obs. is the number of observations. Sample share is the percentage of the sample that usesthe media source. s.d. is standard deviation. Min is minimum value. Max is maximum value. Own Internet is home Internet service not provided by KN.

COMMUNITY NEWS and ADVERTISING characteristics were about "medium." About 58 percent of respondents indicated that they bundled their subscription TV service with the Internet and/or telephone service. The price (p or, $COST$) for the typical media combination ranged from zero to \$447 per month, with an average of \$111.20 per month.[9] Interestingly, about ten percent of the sample indicated that they have contributed \$117, on average, to public radio and/or TV stations during the past twelve months. This is reasonably close to the combined annual costs of membership at 2011. For example, Rocky Mountain PBS offers an annual membership for \$40 and Colorado Public Radio for \$120. These membership costs vary between states.

Because they are self-reported, there may be some concern about the accuracy of the data describing the news service characteristics in our sample. We address these concerns by testing the relationships between our measures of diversity and localism and alternative measures from the FCC (2011) and Gentzkow and Shapiro (2013). Table 3.5 reports the estimates from a simple ordered-probit model of DIVERSITY OF OPINION, MULTICULTURALISM, COMMUNITY NEWS or ADVERTISING on these various alternative measures of diversity and localism for radio, TV, newspapers and the Internet. In general, the evidence indicates that the information reported by survey respondents is a reasonably good proxy for the diversity of news service alternatives in

[9]We used data from consumer's actual new service at home to estimate a hedonic pricing model of COST on DIVERSITY OF OPINION, MULTICULTURALISM, COMMUNITY NEWS, ADVERTISING and controls for demographics and the various media source combinations in our sample. The results, not reported, show that a marginal increase in diversity is valued at $7.46 permonthandamarginaldecreaseinadvertisingisvaluedat 3.83$ per month. The marginal valuations for community news and information on multiculturalism issues are relatively small and not significantly different from zero. These results indicate that market data alone does not exhibit sufficient variation for the precise estimation of all demand parameters for news service and that a mixture of market and experiential data is appropriate.

Table 3.4: Summary Statistics for News Service Characteristics

Feature	Obs.	Mean	s.d.	Min	Max
DIVERSITY OF OPINION	5,131	2.09	0.655	1	3
COMMUNITY NEWS	5,131	1.99	0.711	1	3
MULTICULTURALISM	5,131	1.83	0.705	1	3
ADVERTISING	5,131	2.29	0.682	1	3
COST ($ per month)	5,131	111.2	76.03	0	447
CONTRIBUTION ($ annual)	535	111.5	161.5	0.25	1,500
BUNDLE	3,688	0.576	0.494	0	1

NOTES. 1 = "low, 2 = "medium and 3 = "high for DIVERSITY OF OPINION, COMMUNITY NEWS, MULTICULTURALISM, and ADVERTISING. CONTRIBUTION is value of contributions to public radio and public TV stations during the past 12 months. BUNDLE = 1 when subscription television service is bundled with Internet service and/or other telephone services. Obs. Is the number of observations. s.d. is standard deviation. Min is minimum value. Max is maximum value.

U.S. markets. For example, row two shows a positive correlation between the number of TV stations broadcasting multiple channels and DIVERSITY OF OPINION, row's three and four show positive correlations between the number of non-commercial radio and TV stations and DIVERSITY OF OPINION, and row five shows a positive correlation between the number of different radio formats and DIVERSITY OF OPINION. Row six shows that high newspaper slant, as measured by Gentzkow and Shapiro is correlated with lower DIVERSITY OF OPINION.

3.3.4 Market Structure

We use data from the FCC (2011) to measure media market structure. The important variables of interest are the number of full-power independent TV stations in the market (VOICES) and the total number of full-power independent and non-independent TV stations in the market (STATIONS). VOICES is measured by first combining all the TV outlets within each market. The listing of the unique parent company identifiers of all attributable owners of an outlet ("voiceprint") is then created, sorted alphabetically, and duplicate voiceprints are eliminated. The parent identifier is then used to count the number of voices in the voiceprint for each outlet. Voiceprints composed of a single voice are added to the voice count of the market, while any voiceprint that includes one of the voices counted at the previous stage of the calculation are eliminated. These are voices that are not independent because their voice has been heard on another outlet. This process is sequentially repeated based on the number of voices in the voiceprint. Table 3.6 describes the remaining market

Table 3.5: External Validation of Diversity and Localism

External measures	Diversity	Multicult	Comm News	Adv
Stations with radio	-0.0121 (0.0199)			
Stations with TV	0.0425** (0.0137)			
Non-Comm Radio	0.0093*** (0.002)			
Non-Comm TV	0.0430*** (0.0106)			
Radio Formats	0.0036*** (0.001)			
Gentzkow-Shapiro slant	-3.959*** (1.04)			
Radio with Female Owners		0.0347** (0.0123)		
TV with female owners		0.0364* (0.0184)		
Radio with Minority Owners		0.0034* (0.0013)		
TV with minority owners		0.0254*** (0.0064)		
Commercial radio owned by parents			-0.0004 (0.0005)	
TV owned by parents			-0.0018 (0.0074)	
Internet connections > 200 kbps up and down	0.666** (0.229)	0.462 (0.258)	0.104 (0.18)	0.104 (0.18)
Internet connections > 200 up and 728 down	0.712*** (0.214)	0.608*** (0.255)	0.121 (0.176)	0.193 (0.153)

NOTES. Ordered probit model of Diversity of Opinion, Multiculturalism, Community News or advertising on external measure is estimated by weighted maximum likelihood. Robust standard errors in parentheses. ***denotes significant at the one percent level. **denotes significant at the five percent level. *denotes significant at the ten percent level. All external measures are from the FCC (2011), except the measure of slant, which is from Gentzkow and Shapiro (2010). Slant is the absolute value of the slant toward Republican or Democrat by local newspapers. Multicast is the number of stations that broadcast multiple program streams. Estimated cutoff parameters are not reported. Number of observations in rows 1-5 and 7-12 is 5,102. Number of observations in row 6 is 4,616. Number of observations in row 13 is 5,108. Number of observations in row 14 is 5,084.

structure variables considered in this analysis.

Table 3.6: Media Market Structure

Variable	Description
HOUSEHOLDS	Number of households in the market.
NEWSPAPERS	Number of daily newspapers that publish in a county in the market.
RADIO STATIONS	Number of radio stations in the market.
STATIONS	Number of full-power TV stations in the market.
MEDIA OUTLETS	NEWSPAPERS plus RADIO STATIONS plus STATIONS.
NEWSPAPER VOICES	Number of parent entities owning a newspaper in a market.
RADIO VOICES	Number of independent radio voices in the market.
VOICES	Number of independent TV voices in the market.
MEDIA VOICES	NEWSPAPER VOICES plus RADIO VOICES plus VOICES.
TV-NEWSPAPER VOICES	Number of independent newspaper and TV voices in the market.
TV-RADIO VOICES	Number of independent radio and TV voices in the market.

Table 3.7 presents summary statistics. Our sample covers 203 of the nation's 210 television markets.[10] As of December, 2009, the total number of newspaper, radio, and TV outlets ranged from four to 291, with an average of 139 per market. On average, about 81 percent of media outlets are radio stations, which partially reflects the geographical definition of a TV market which can include several radio markets. When examining the market structure data at the 75^{th} percentile, we observe that most markets are served by about 182 or fewer media outlets. The bottom panel in Table 3.6 shows a similar pattern for small TV markets with five or fewer stations. At December, 2009, the total number of newspaper, radio and TV outlets in small markets ranged from four to 86, with an average of 47 per market. On average, about 82 percent of media outlets in small markets are radio stations, and as indicated by the 75th percentile, most small markets are served by about 57 or fewer media outlets.

The number of TV stations (STATIONS) ranges from one to 27 across the U.S., with most markets having five or more TV stations. As expected, small markets have limited variety and are typically served by one station from the "big four" national networks, ABC, CBS, FOX and NBC, plus one public broadcasting and/or educational station such as PBS. For example, Rochester, New York is comprised of 392,150 TV households and is served by ABC, CBS, FOX, NBC and PBS. In

[10] Television Market Area or "market" is a geographical region where all households receive the same offerings from TV stations. The seven markets outside our sample are: Bend, OR; Fairbanks, AK; Grand Junction, CO; Missoula, MT; North Platte, NE; Ottumwa, IA - Kirksville, MO; and Presque, ME. All seven are small markets with five or fewer TV stations. As shown in Table 3.6, the remaining small markets in our sample cover 8.43 percent of households. FCC (2011) data show that 8.37 percent of population households were in small markets at December, 2009.

Table 3.7: Summary Statistics for Media Market Structure

Variable	Markets	Mean	s.d.	Min	25th	75th	Max
HOUSEHOLDS	203	1,670,158	1,842,396	4,145	447,396	2,228,143	7,444,659
SMALL MARKETS	203	0.084	0.278	0	n.a.	n.a.	1
MEDIA OUTLETS	203	138.7	71.25	4	80	182	291
MEDIA VOICES	203	73.11	35.97	3	44	97	152
NEWSPAPERS	203	12.76	8.206	0	6	19	32
RADIO STATIONS	203	113.2	59.41	3	64	157	241
STATIONS	203	12.74	5.879	1	8	17	27
NEWSPAPER VOICES	203	7.634	4.076	0	4	10	19
RADIO VOICES	203	55.12	28.75	2	31	73	119
VOICES	203	10.36	4.626	1	7	13	22
TV-NEWSPAPER VOICES	203	11.91	4.758	1	8	15	24
TV-RADIO VOICES	203	63.06	30.95	2	38	85	129

contrast, New York is comprised of 7,493,530 TV households and is served by 23 stations. These include multiple channels from the big four networks, several public broadcasting and educational channels (e.g., PBS, Public TV), several non-English language channels (e.g., TeleFuturo, TeleMundo), several other independent stations (e.g., Mountain Broadcasting, Retro TV) and a religious channel (Trinity).

3.4 Demand Estimates

The choice data described in Section 3.1 are used to estimate the model of household utility (equation 2) from their local news service. Because 29 respondents do not have geographical identifiers and could not be assigned to their appropriate TV market in Section 5, they are dropped from the final sample of 5,131. Since each of the choice scenarios represent information on preferences from three alternatives, A, B, and actual news service at home, the sample size for econometric estimation is 5,1028 = 40,816. Table 2 showed some demographic differences between our final sample and the population. We remedy this possible source of bias in our results by estimating the discrete-choice model by weighted maximum likelihood, where the contribution to the log-likelihood is the post-stratification weight times the log of the choice probability for the choice occasion.

Table 3.8 reports weighted maximum likelihood estimates of the household utility model. Because consumers may have heterogeneous preferences for unmeasured aspects of news service, we estimate utility with an alternative-specific constant to capture differences in tastes between the actual and hypothetical (A and B) news services. For purpose of comparison, in model (i) we begin by reporting estimates from a standard conditional logit model with fixed marginal utility parameters. Model (ii) displays estimates from a mixed logit model specification where the four non-price marginal utility parameters are assumed to be independently normally distributed.[11] Preferences may be correlated, for example, consumers who like more diversity of opinion may also like more information on women and minorities. Accordingly, the mixed logit model (iii) permits correlation between the non-price parameters. Model (iv) reports estimates from a mixed logit model specification with correlated non-price parameters plus the two interactions, COSTxMED_INCOME and COSTxHIGH_INCOME.[12][13]

The data fit all model specifications reasonably model well as judged by the sign and statistical significance of most parameter estimates. We focus our discussion on the results from model (iv) because that model is the most general, permitting both correlation among the random parameters and the marginal disutility of cost to vary by income, as specified in equation 2. The mean of each of the random marginal utility parameters for DIVERSITY OF OPINION, MULTICULTURALISM and COMMUNITY NEWS are positive and significant at the one percent level, while the mean of the random parameter for ADVERTISING is negative and significant. These estimates imply that the representative consumer's utility increases when there is more diversity in the reporting of news, more information on women and minorities, more information on community news, and less space and/or time devoted to advertising. The fixed parameter for COST is negative and the corresponding parameters for COSTxMED_INCOME and COSTxHIGH_INCOME are positive. These estimates imply that consumer's utility decreases when the dollar amount paid for their news service increases but that the effect diminishes with increases in household income.

The standard deviations of each of the random marginal utility parameters are significant at the

[11] All mixed logit models were estimated by simulated maximum likelihood using 100 Halton draws. For robustness, we estimated several model specifications using 500 draws and the results are similar. The estimated variance-covariance matrices from the correlated random parameters model specifications are not reported but are available from the authors upon request.

[12] We also estimated a variant of model (iv) that included an additional interaction between an indicator of college education and COST. This additional interaction was not statistically significant at conventional levels and the results, not reported, are similar to those reported in Table 3.8.

[13] There are no systematic biases towards a specific alternative within the choice scenario. Consumers chose their actual news service at home 29.1 percent of the time, news service alternative A 34.4 percent of the time, and news service alternative B 36.5 percent of the time. The number of seconds it took respondents to answer each choice occasion remained essentially constant over the eight choice occasions. Because some of our data are from repeated choices, we also need to be concerned with survey fatigue (Savage and Waldman, 2008). For a robustness check, we estimated all model specification's (i) through (v) on the data for the first four choice questions versus the second four questions. The results, not reported, show reasonably similar estimates for the two subsamples of data. There is no systematic pattern that could be taken as evidence of survey fatigue.

Table 3.8: Mixed Logit Estimates of the Demand for Local News

	Model (i)	Model (ii)	Model (iii)	Model (iv)
Cost	-0.0198***	-0.0280***	-0.0365***	-0.0412***
	(0.00018)	(0.0003)	(0.0007)	(0.0008)
Cost x Med Income			0.00394***	0.00527***
			(0.0009)	(0.00095)
Cost x High Income			0.0114***	0.0128***
			(0.0007)	(0.0008)
Diversity of Opinion	0.383***	0.433***	0.443***	
	(0.0091)	(0.0161)	(0.0162)	
Community News	0.461***	0.433***	0.449***	
	(0.0089)	(0.0140)	(0.0144)	
Multiculturalism	0.0122	0.0154	0.0407***	
	(0.00887)	(0.0145)	(0.0146)	
Advertising	-0.357***	-0.227***	-0.244***	
	(0.0104)	(0.0162)	(0.0163)	
Med Diversity of Opinion				0.748***
				(0.0315)
High Diversity of Opinion				0.991***
				(0.0367)
Med Community News				0.894***
				(0.0330)
High Community News				1.116***
				(0.0340)
Med Multiculturalism				0.253***
				(0.0263)
High Multiculturalism				0.147***
				(0.0318)
Med Advertising				-0.169***
				(0.0230)
High Advertising				-0.739***
				(0.0394)
Observations	40,816	40,816	40,816	40,816
Likelihood	-59,453	-32,714	-32,477	-32,523

Notes. Standard errors in parentheses. Estimated by simulated weighted maximum likelihood. Model (i) is estimated with the conditional logit model. (ii) through (iv) are estimated with the mixed logit model.
* $p < .10$, ** $p < .05$, *** $p < .01$

one percent level, indicating that tastes vary in the population. Together, the estimated means and standard deviations of the random parameters provide useful policy information on the percentage of the population that place a positive value on the non-price characteristics of news service. The mean and standard deviation of the parameter estimator for DIVERSITY OF OPINION are 0.443 and 0.801, respectively. Using the cumulative normal distribution, one possible interpretation is that about 70 percent of the population prefer more different viewpoints in the reporting of news and 30 percent prefer fewer viewpoints. Similar calculations show that about 80 percent of the population prefer more community news, and more news that reflects the interests of women and minorities is preferred by about one-half of the population. Approximately two-thirds of the population prefer having less advertising.

Although our description of advertising does not measure content, it does measure the amount of space on a newspaper or web page, or the amount of air time devoted to commercial advertising on radio or TV. Given this definition and information on public news consumption from the Pew Research Center, we use our demand estimates to shed light on the value of informative vs. non-informative advertising. Given that 58 percent of the U.S. public get their news from the TV, the estimated negative valuations for ADVERTISING likely reflect the consumption of general, all-purpose advertising delivered by traditional media such as radio and TV. In other words, most consumers will indicate their distaste for non-informative advertisements because they do not want to view them or listen to them. In contrast, the estimated positive valuations likely reflect the consumption of more informative, targeted advertisements delivered by new media such as the Internet, Smartphone and Video-on-Demand (VoD). Here, consumers indicate their preference for advertisements because they are positively informed about something specific to their needs and/or they have some choice in the advertisements they actually view.[14]

In this discussion the coding of the four non-price features in the household utility function is linear, which implies that the marginal utilities are the same when moving from low to medium and from medium to high levels. We now relax this restriction by replacing each of the four non-price characteristics with a pair of dichotomous variables. For example, MEDIUM DIVERISTY OF OPINION equals one when DIVERISTY OF OPINION equals “medium” and zero otherwise,

[14]For example, Comcast cable TV network targets specific customer types through its VoD service and then permits the customer to select the advertisements she or he wants to view with their remote control. See http://www.comcastspotlight.com/advertising-solutions/on-demand.

and HIGH DIVERISTY OF OPINION equals one when DIVERISTY OF OPINION equals "high" and zero otherwise. Therefore, the estimated parameter on MEDIUM DIVERISTY OF OPINION measures the change in utility from moving from information on news and current affairs in the household's overall news service reflecting only one viewpoint (low diversity, the omitted category) to a few different viewpoints (medium diversity). The estimated parameter on HIGH DIVERISTY OF OPINION measures the change in utility from moving from information on news and current affairs reflecting only one viewpoint to many different viewpoints (high diversity). This approach to estimating non-linear valuations is used for all other non-price characteristics of the local news service.

Mixed logit estimates of the utility model with non-linear preferences and with correlated non-price parameters plus COSTxMED_INCOME and COSTxHIGH_INCOME are presented in Model (v) of Table 3.8. Focusing on the means of each of the random marginal utility parameters, the results indicate declining marginal utility for the representative consumer with respect to diversity of opinion, multiculturalism and community news. WTP estimates by household income for both the linear and the nonlinear models are presented in Table 3.9. In column three we observe that the representative medium-income consumer is willing to pay \$20.82 per month for an improvement in diversity of opinion from low to medium, but only another \$6.76 per month for an additional improvement to high diversity of opinion. Similarly, the representative medium-income household is willing to pay \$24.88 per month for an initial improvement in information on community news and events from low to medium, but only another \$6.18 per month for an additional improvement to high. The marginal utility estimates for multiculturalism indicate that households value an improvement in information that reflects the interests of women and minorities from low to medium (i.e., WTP = \$7.04) more than an improvement from low to high (i.e., WTP = \$4.09). In other words, the representative medium-income household wants more, but not a lot more information reflecting the interests of women and minorities. The marginal utility estimates for advertising indicate a similar pattern to diversity of opinion and community news, albeit in reverse. The representative household is willing to pay about \$15.87 per month for a move from high to medium advertising, but only an additional \$4.70 per month to move from medium to low advertising.

Table 3.9: Willingness-to-Pay by Household Income

	Low < $25,000	$25,000 ≤ Medium < $50,000	$50,000 ≤ High income
Linear preferences			
Diversity	$12.24	$13.74	$17.79
	(0.69)	(0.78)	(1.01)
Comm News	$12.41	$13.95	$18.03
	(0.58)	(0.64)	(0.85)
Multiculturalism	$1.15	$1.27	$1.64
	(0.61)	(0.67)	(0.87)
Advertising	-$6.75	-$7.56	-$9.78
	(0.6)	(0.66)	(0.87)
Non-linear preferences			
Med Div of Op	$18.16	$20.89	$26.38
	(1.01)	(1.12)	(1.43)
High Div of Op	$24.08	$27.67	$34.99
	(1.36)	(1.54)	(2.01)
Med CommNews	$21.74	$24.92	$31.53
	(1.06)	(1.24)	(1.51)
High CommNews	$27.17	$31.09	$39.38
	(1.22)	(1.4)	(1.71)
Medium MultiC	$6.15	$7.05	$8.92
	(0.72)	(0.83)	(1.02)
High MultiC	$3.60	$4.06	$5.22
	(1.11)	(1.25)	(1.65)
Med Advertising	-$4.13	-$4.72	-$5.98
	(0.47)	(0.54)	(0.68)
High Advertising	-$17.97	-$20.66	-$26.07
	(1.38)	(1.56)	(1.94)

NOTES. Bootstrapped standard errors are in parentheses. Willingness-to-pay is calculated using the mean of each of the random marginal utility parameters and the marginal disutility of COST. The marginal disutility of COST varies by household income and is $\beta_1 + \beta_M$MED_INCOME + β_HHIGH_INCOME, where MED_INCOME equals 1 when household income is greater than $25,000 and less than $50,000 and 0 otherwise, and HIGH_INCOME equals one when household income is greater than $50,000 and zero otherwise. Linear calculations use utility estimates from model (iv) in Table 7. Non-linear calculations use utility estimates from model (v) in Table 7. The parentheses on MEDIUM DVERTISING indicate WTP to move from a medium to a low level of advertising. The parentheses on HIGH ADVERTISING indicate WTP to move from a high to a low level of advertising.

3.5 Policy Experiment

The demand estimates provide information on the expected societal benefits from increased media diversity and localism. The question of interest now is how do these benefits change with regulatory interventions that shape media market structure? We shed light on this question by estimating the relationships between the number of TV stations in the market and the amount of diversity, localism and advertising supplied within each household's news service. The resulting supply response parameters are then combined with WTP calculations to conduct a simple policy experiment that measures the impact on consumer welfare from a change in media market structure that reduces the number of independent TV voices by one.

3.5.1 The Supply of News Services

Previous studies of media markets typically use academic and industry databases from BIA Financial Networks, Neilson Media Research and ProQuest Newsstand to measure the quantity and quality of news provided by newspapers, radio and TV stations. For example, Yan and Napoli (2006) and Crawford (2007) count the minutes of local programming provided by TV stations. Groseclose and Milyo (2005) measure media bias by counting the number of times a particular newspaper or TV station cites various political think tanks and then compare this with the number of times that members of Congress cite the same groups. Gentzkow and Shapiro (2013) measure diversity with an index that measures the similarity of a newspaper's language to that of a congressional Republican or Democrat.[15] Because we are investigating a household's news services from all of their media sources, similar measures are not desirable for this study. Instead, we use information on consumer's news service at home to measure the characteristics supplied by news service alternatives in different TV markets.

Consider a reduction in the number of independent TV voices in a market as it impacts the single news service characteristic diversity of opinion (d). A simple representation of the diversity

[15] Greenstein and Zhu (2012) used a similar method to Gentzkow and Shapiro to measure the slant of 28,000 Wikipedia articles about US politics.

of opinion produced by alternative j for consumer n in television market m is:

$$\begin{aligned} d^*_{njm} =& \delta_1 VOICES_m + \delta_2 STATIONS_m + \delta_3 (VOICES_m x STATIONS_m) + \tau D_n \\ &+ \gamma Z_j + v_{njm} \end{aligned} \tag{3.4}$$

where d^*_{njm} is the unobserved continuous index of the diversity of opinion in respondent n's media, $VOICES_m$ is the number of independent TV voices in the market, $STATIONS_m$ is the number of TV stations in the market, D_n is a vector of consumer-specific demographic controls, Z_j is a vector of news service controls, the δ's, τ and γ are parameters, and v is an independently and identically normally distributed error term with zero mean and constant variance σ^2_v. The interaction term is included to measure the different impacts from a change in market structure in small- versus large-TV markets. The D_n vector measures the head of the household's age (AGE = 1 if 18 - 24 years; 2 if 25 - 34; 3 if 35 - 44; 4 if 45 - 54; 5 if 55 - 64; 6 if 65 - 74; 7 if 75 years or over), education (EDUC = 1 if less than high school; 2 if high school; 3 if some college; 4 if bachelor's degree or more), gender (GENDER = 1 if female; 0 otherwise), household income (INCOME = 1 if less than \$10,000; 2 if \$10,000 - \$24,999; 3 if 25,000 - \$49,999; 4 if \$50,000 - \$74,999; 5 if \$75,000 or more), and race (RACE = 1 if white; 0 otherwise). The Z_j vector includes dummy variables to control for the 16 different media source combinations in our sample that are comprised from newspapers, radio, TV, the Internet, and Smartphone.[16]

The respondent reports one of three possible levels for the diversity of opinion feature, low, medium or high, based upon her or his level of d^*_{njm}:

$$d_{njm} = \left\{ \begin{array}{ll} low & d^*_{njm} \leq 0 \\ medium & 0 < d^*_{njm} \leq \mu \\ high & \mu < d^*_{njm} \end{array} \right\} \tag{3.5}$$

where μ is the normalized unknown level of d^*_{njm} above which respondents report a high level for diversity of opinion. Given v is normally distributed, equation's 4 and 5 represent the conventional ordered probit model, which can be estimated by maximum likelihood (McKelvey and Zavoina,

[16]For a robustness check, we specified an alternative set of dummy variables that also controlled for subsets of radio (i.e., satellite and broadcast radio) and TV (i.e., cable, satellite and broadcast TV). Ordered probit estimates of media supply responses, and estimates of the impacts on consumer welfare from a change in market structure, not reported here, are similar to those presented in Tables 3.10 and 3.11 below.

Table 3.10: Second-Stage Ordered Probit Estimates of Relationship between News Service Supply and Market Structure

	DIV OF OPINION	COMMUNITY NEWS	MULTIC	ADVERT
VOICES	0.0682***	0.0463*	0.0941***	0.0497**
	(0.0263)	(0.027)	(0.025)	(0.026)
VOICES	-0.0001	-0.0017**	-0.0012	-0.0011
xSTATIONS	(0.001)	(0.001)	(0.001)	(0.001)
STATIONS	-0.0124	0.0023	-0.0311**	-0.0008
	(0.0173)	(0.0166)	(0.0155)	(0.0147)
AGE	0.0409***	0.0828***	0.0263**	0.111***
	(0.0098)	(0.0165)	(0.0104)	(0.0112)
EDUC	0.142***	0.0828***	0.1250***	0.0999***
	(0.0185)	(0.0165)	(0.0152)	(0.0208)
GENDER	-0.0412	0.1310***	0.0516	0.0188
	(0.0327)	(0.0284)	(0.0357)	(0.026)
INCOME	0.0595***	-0.0013	-0.0275**	0.0295**
	(0.0128)	(0.0144)	(0.0139)	(0.0121)
RACE	0.0582***	-0.1210***	-0.083*	0.2210***
	(0.0334)	(0.0382)	(0.041)	(0.0446)
$\hat{\lambda_m}$	-0.0602**	-0.0256*	-0.0414	-0.0194
	(0.026)	(0.0173)	(0.0257)	(0.0159)
Likelihood	-4,844.40	-5,218.40	-5,182.80	-4,910.80
Mean Δ in Percentage				
$\frac{\Delta P_L}{\Delta Voices}$	0.0142	0.0077	0.0289	0.0076
$\frac{\Delta P_M}{\Delta Voices}$	0.0028	-0.0003	-0.0096	0.0060
$\frac{\Delta P_H}{\Delta Voices}$	-0.0170	-0.0074	-0.0193	-0.0136

NOTES. Estimated by weighted maximum likelihood. Bootstrapped standard errors in parentheses. ***denotes significant at the one percent level. **denotes significant at the five percent level. *denotes significant at the ten percent level. Estimated cutoff parameters and estimated parameters for the media alternative dummy variables are not reported. Number of observations is 5,102. Sample mean probabilities are calculated from each individual respondent's predicted probabilities. $\Delta P_L = P_{L1} - P_{L0}, \Delta P_M = P_{M1} - P_{M0}, \Delta P_H = P_{H1} - P_{H0}, and \Delta X = \Delta VOICES = -1$. $\hat{\lambda_m}$ is the modified error correction term calculated from the parameter estimates from the first-stage profit equation.

Table 3.11: Impact on Consumer Welfare From a Change in Market Structure

Size	Pop. Share	DIV	MCult	Adv	CNews	Div	MCult	Adv	CNews	Total	Total - ADV
		Average consumer welfare per month (Dollars per month)				Annual aggregate welfare in market (Dollars in millions)					
5	0.05	-0.55	-0.19	0.34	-0.43	-29.65	-10.50	18.21	-23.13	-45.07	-63.28
		(0.05)	(0.06)	(0.04)	(0.03)	(2.61)	(3.15)	(2.42)	(1.57)		
6	0.061	-0.53	-0.19	0.33	-0.39	-35.15	-12.33	21.56	-25.75	-51.67	-73.23
		(0.06)	(0.07)	(0.05)	(0.03)	(4.05)	(4.90)	(3.54)	(2.24)		
7	0.091	-0.54	-0.20	0.33	-0.38	-52.72	-19.50	32.13	-37.10	-77.19	-109.32
		(0.05)	(0.06)	(0.05)	(0.03)	(4.78)	(6.07)	(4.48)	(2.51)		
8	0.081	-0.51	-0.18	0.32	-0.35	-44.71	-15.73	27.95	-30.62	-63.12	-91.07
		(0.05)	(0.06)	(0.05)	(0.03)	(4.33)	(5.23)	(4.01)	(2.27)		
9	0.095	-0.49	-0.17	0.30	-0.31	-29.72	-10.62	18.34	-19.09	-41.09	-59.43
		(0.06)	(0.07)	(0.05)	(0.03)	(3.73)	(4.35)	(3.09)	(1.73)		
10	0.056	-0.49	-0.18	0.30	-0.31	-29.72	-10.62	18.34	-19.09	-41.09	-59.43
		(0.06)	(0.07)	(0.05)	(0.03)	(3.73)	(4.35)	(3.09)	(1.73)		
11	0.099	-0.48	-0.17	0.29	-0.30	-51.70	-18.67	31.59	-31.80	-70.57	-102.16
		(0.04)	(0.05)	(0.04)	(0.02)	(4.36)	(5.57)	(3.99)	(2.14)		
12	0.069	-0.47	-0.18	0.28	-0.28	-35.22	-13.16	20.90	-20.69	-48.17	-69.07
		(0.04)	(0.05)	(0.04)	(0.02)	(4.36)	(5.57)	(3.99)	(2.14)		
13	0.024	-0.46	-0.16	0.28	-0.26	-11.90	-4.21	7.21	-6.72	-15.62	-22.83
		(0.08)	(0.10)	(0.06)	(0.03)	(1.95)	(2.52)	(1.62)	(0.83)		
14	0.093	-0.43	-0.14	0.27	-0.24	-42.81	-14.30	27.33	-23.74	-53.52	-80.85
		(0.04)	(0.06)	(0.04)	(0.02)	(4.34)	(5.63)	(3.65)	(1.74)		
15	0.03	-0.43	-0.15	0.25	-0.22	-14.01	-4.83	8.24	-7.08	-17.68	-25.92
		(0.08)	(0.09)	(0.06)	(0.03)	(2.68)	(3.08)	(2.11)	(0.90)		
16	0.079	-0.40	-0.14	0.26	-0.20	-34.63	-11.77	22.58	-17.50	-41.31	-63.90
		(0.05)	(0.06)	(0.04)	(0.02)	(4.14)	(5.43)	(3.46)	(1.35)		
17	0.072	-0.41	-0.14	0.24	-0.18	-31.60	-11.01	18.97	-14.32	-37.95	-56.93
		(0.05)	(0.07)	(0.04)	(0.02)	(3.65)	(5.11)	(3.22)	(1.30)		
18	0.043	-0.40	-0.14	0.24	-0.17	-18.62	-6.72	11.06	-7.87	-22.15	-33.20
		(0.06)	(0.08)	(0.05)	(0.02)	(2.99)	(3.81)	(2.25)	(0.88)		
19	0.026	-0.40	-0.15	0.24	-0.15	-11.12	-4.10	6.72	-4.34	-12.84	-19.57
		(0.07)	(0.10)	(0.06)	(0.02)	(2.08)	(2.73)	(1.75)	(0.55)		
20	0.032	-0.36	-0.13	0.20	-0.08	-12.53	-4.52	6.93	-2.70	-12.81	-19.74
		(0.03)	(0.04)	(0.02)	(0.01)	(1.01)	(1.26)	(0.70)	(0.18)		
Total	1	-0.47	-0.17	0.29	-0.28	-506.12	-179.73	311.06	-306.08	-680.87	-991.93
		(0.01)	(0.01)	(0.01)	(0.01)	(15.35)	(15.35)	(10.46)	(6.82)		

NOTES. Bootstrapped standard errors in parentheses. The change in market structure is a one-unit reduction in the number of independent TV voices in the market, all other things held constant. There are 90,193,905 population households in markets from five to 20 TV stations (FCC, 2011). Pop. share is the number of population households in the market divided by population households. DIV is diversity of opinion in the reporting of information, MCULT is coverage of multiculturalism issues, ADV is amount of space or time devoted to advertising, and CNEWS is amount of information on community news and events. Total losses of $832.1 million are the sum of the individual market losses.

1975). We estimate equation 4 to obtain the relationships between the number of TV stations in the market and the four non-price characteristics of news service, and use these estimates to approximate the supply-side responses from media outlets.

It is tempting to multiply the estimated δ_1 and δ_3 from equation 4 by the estimated b_1 from equation 2, to calculate the mean value to society from a change in the number of independent TV voices that affects the market's provision of diversity of opinion. However, this would result in an estimate of $\frac{b_1}{\sigma}\frac{\delta_1+\delta_3 STATIONS_m}{\sigma_v}$, where σ_v is the standard deviation of the errors in equation 4. This is not the effect we are interested in. The problem is that we cannot observe the scale of diversity of opinion. Instead, we apply a new technique to our estimates, explained below, which takes advantage of the fact that we do not need to estimate the scale of diversity of opinion. This alternative approach uses our sample estimates from equations 2 and 4 to predict how changes in the number of independent TV voices affect consumer's expected benefit from the amount of diversity of opinion supplied in their local news service. For ease of notation, we let X = VOICES and drop all subscripts that indicate consumers, alternatives, and markets. The representative consumer's expected benefit from the diversity of opinion in their local news service is:

$$E[B_d(X)] = P_{dL}(X)v^*_{dL} + P_{dM}(X)v_{dM} * +P_H(X)v^*_{dH} \tag{3.6}$$

where $P_{dL}(X)$ is the probability that the consumer will be in the low diversity of opinion state, $P_{dM}(X)$ is the probability that the consumer will be in the medium state, $P_{dH}(X)$ is the probability that the consumer will be in the high state, and v^*_{dL}, v^*_{dM} and v^*_{dH} are consumer valuations for low, medium and high diversity of opinion.

We do not observe v^*_{dL}, v^*_{dM} and v^*_{dH}. However, we are able to estimate from equation 2 the consumer's WTP for a change from low to medium diversity of opinion (Δv_{dM}), and the WTP for a change from low to high diversity (Δv_{dH}). Writing $v^*_{dM} = v^*_{dL} + \Delta v_{dM}$ and $v^*_{dH} = v^*_{dL} + \Delta v_{dH}$ and substituting this expression into the consumer's expected benefit equation 6 gives $E[B_d(X)] = P_{dL}(X)v^*_{dL} + P_{dm}(X)(v^*_{dL} + \Delta v_{dm}) + P_{dH}(X)(v^*_{dL} + \Delta v_{dH})$. The effect of a change in X on the expected benefit from diversity of opinion is:

$$\begin{aligned}\frac{\Delta E[B_d(X)]}{\Delta X} &= \frac{\Delta P_{dL}}{\Delta X}v^*_{dL} + \frac{\Delta P_{dM}}{\Delta X}(v^*_{dL} + \Delta v_{dM}) + \frac{\Delta P_{dH}}{\Delta X}(v^*_{dL} + \Delta v_{dH}) \\ &= (\frac{\Delta P_{dL}}{\Delta X} + \frac{\Delta P_{dM}}{\Delta X} + \frac{\Delta P_{dH}}{\Delta X})v^*_{dL} + \frac{\Delta P_{dM}}{\Delta X}\Delta v_{dM} + \frac{\Delta P_{dH}}{\Delta X}\Delta v_{dH} \\ &= \frac{\Delta P_{dM}}{\Delta X}\Delta v_{dM} + \frac{\Delta P_{dH}}{\Delta X}\Delta v_{dH}\end{aligned} \tag{3.7}$$

where $\frac{\Delta P_{dM}}{\Delta X}$ and $\frac{\Delta P_{dH}}{\Delta X}$ measure the effects of a change in X on the predicted probability of being in the medium and the high diversity of opinion states, and $(\frac{\Delta P_{dL}}{\Delta X} + \frac{\Delta P_{dM}}{\Delta X} + \frac{\Delta P_{dH}}{\Delta X} = 0)$, which follows from the requirement that the three probabilities sum to one. The derivation of this result shows clearly that the change in expected consumer welfare is a function of only WTP for a change out of the low level of diversity and the changes in probability for the supply of medium and high levels of diversity.

Equation 7 provides the basis for calculating the value to society from a change in market structure that affects the provision of diversity of opinion in local media markets. Estimates of Δv_{dM} and Δv_{dH} for the typical consumer are obtained from the marginal WTP calculations in Table 3.9. We then use our estimated coefficients from the ordered probit model of equation 4 and the sample data to calculate the predicted probability distributions for low, medium and high diversity of opinion in the "before" environment. Holding all other things constant, we then reduce the number of independent TV voices by one in the sample data to approximate the change in market structure, and re-calculate the predicted probability distributions for low, medium and high diversity of opinion in the "after" environment. The difference in before-and-after probabilities are used to form the change in probabilities, $\frac{\Delta P_{dM}}{\Delta X}$ and $\frac{\Delta P_{dH}}{\Delta X}$. These calculations are repeated for the multiculturalism, community news, and advertising characteristics, and then aggregated to reflect the general population.

3.5.2 Relationship Between News Services Characteristics and Market Structure

Because unobserved cost and demand factors affect both media market structure and the supply of news service characteristics, the estimated coefficient on VOICES in equation 4 is likely to suffer from omitted variable bias. For example, a market with higher unobserved costs of producing advertising will be less profitable and will attract fewer TV stations. This market may also have more advertising because stations need additional revenue to cover their higher costs. A standard ordered probit model would bias the estimated relationship between ADVERTISING and VOICES in a negative direction. We account for this endogeneity with a two-stage selection model similar to Mazzeo (2002b), Singh and Zhu (2008), and Chen and Savage (2011). In the first stage, we estimate an ordered probit model that relates the latent profits of market m to market size, variable profits per TV household, and fixed costs.[17] Estimated parameters from the first stage are used to construct a modified error correction term ($\hat{\lambda_m}$) similar to the inverse Mills ratio in Heckman's (1979) sample selection model. In the second stage, we estimate equation 4 with an ordered probit model of the non-price news characteristic of interest, DIVERISTY OF OPINION, MULTICULTURALISM, COMMUNITY NEWS or ADVERTISING, on VOICES, STATIONS, VOICESxSTATIONS, D, Z and $\hat{\lambda}$. Since unobserved factors are controlled for by the correction term, the estimated relationship between the news service characteristics and the number of independent TV stations in the market will be consistent. Detailed description of the first stage model's variables, data and estimation results are available from the authors upon request. [18]

Table 3.10 presents the second-stage estimates of equation 4 with the modified correction term ($\hat{\lambda_m}$) included as an additional variable. Because ($\hat{\lambda_m}$) is estimated in the first stage, the asymptotic variance of the second-stage estimator is not valid. We report bootstrapped standard errors for supply responses with 100 replications.[19] We also report the original supply response coefficients, which are recovered from the two-stage model using the method described by (Imbens and Wooldridge, 2007). The estimated coefficients on the modified correction term are statistically significant for the two diversity characteristics, DIVERISTY OF OPINION and MULTICULTURALISM, and marginally insignificant for the localism characteristic, COMMUNITY NEWS. These results suggest that it is important to account for the potential correlation between the unobserved components of the supply of news service characteristics, and TV station profits.

[17]Because they are not observed, latent profits are approximated by the number of independent TV voices in the market (VOICES). Note also that we do not formally model product differentiation in TV markets, e.g., independent vs. non-independent firms, or large vs. small firms, as in the case of Mazzeo (2002b) and (Schaumans and Verboven, 2011). Our goal is to obtain parameter estimates from the first-stage profit equation to calculate the modified correction term (λ_m) for inclusion in equation 4.

[18]The first-stage profit results indicate that there are more independent TV stations in markets with more households, higher population growth, higher household income and more female population. There are fewer stations in markets with a lot of snow, sleet and freezing rain, which increases the fixed costs of constructing and maintaining a more durable broadcast antennae.

[19]For robustness, we bootstrapped the standard errors with 500 replications and the results are similar.

Focusing on the important variable of interest, we observe that that estimated coefficients on VOICES are positive for all non-price news characteristics, while the estimated coefficients on VOICESxSTATIONS are negative. These results are consistent with Mazzeo (2003), Goolsbee and Petrin (2004), Matsa (2011b) and Olivares and Cachon (2009), and suggest that in markets with one fewer independent TV station, consumers are more likely to have less diversity of opinion, multiculturalism and community news in their news service. For example, the sample means of the predicted probabilities of supply presented in the bottom panel of Table 3.10, show that following the change in market structure, the percentage of households in a low diversity of opinion state will increase by 1.6, the percentage of households in a medium state will increase by three, and the percentage of households in a high state will decrease by 1.9. The results with respect to diversity of opinion, multiculturalism, and community news are reasonably intuitive. Consolidation of TV stations is associated with the softening of media competition and the provision of less diversity and less local news, which is costly to produce.[20]

Table 3.10 also shows that markets with one fewer independent TV station are more likely to have less advertising. This is consistent with similar empirical findings for radio and TV markets which find that broadcasters in concentrated markets scale back the amount of advertising but charge higher advertising rates. For example, Crawford (2007) finds that independent TV stations provide more advertising per program but charge lower prices to advertisers. Brown and Alexander (2005) find a positive correlation between TV market concentration and the price of advertising per viewer. Following Cunningham and Alexander (2004), they argue that when consumer's elasticity of TV viewing with respect to advertising is weak, a decrease in the fraction of broadcast time devoted to advertising can lead to a decrease in the overall amount of advertising supplied and an increase in advertising rates. Drushel (1998) finds that following the Act, increased radio station concentration was positively correlated with higher advertising rates.

3.5.3 Consumer welfare and market structure

We use our marginal WTP estimates from Table 3.9, predicted supply probabilities from Table 3.10 and the expected benefit equation 7, to measure the impact on consumer welfare from the

[20]By definition, a reduction in the number of independent TV stations means there are fewer viewpoints in the market, and as a result, less diversity of opinion.

change in media market structure. Table 3.11 and Figure 3.1 present estimates of the impact on consumer welfare from a marginal decrease in the number of independent TV stations for all market sizes ranging from five to 20 TV stations. Columns three through six of Table 3.11 report average consumer welfare per month and columns seven through twelve report annual aggregate welfare.[21] The first interesting observation is that the average welfare effects per month depend on market size, with smaller markets having larger effects in absolute terms. The intuition for this finding is clear. The impact from the loss of an independent voice in the market will be more acute when there are fewer competitors to fill the void. As a result, the average consumer in a small market loses \$0.83 per month, whereas the average consumer in a large market loses \$0.37 per month. These losses are equivalent to about \$45 million annually for all small-market households in the U.S. and \$13 million for all large-market households.[22] If the change in market structure occurs in all markets, for example, if two of the big four networks ABC, CBS, FOX or NBC consolidated, annual aggregate losses nationwide would be about \$680 million. For comparison, this represents about seven percent of the total operating costs for CBS in 2010.[23]

Given the WTP estimates in Table 3.9, it is not surprising that the average welfare losses per month from DIVERSITY OF OPINION and COMMUNITY NEWS are greater than MULTICULTURALISM in almost all markets. However, while DIVERSITY OF OPINION continues to have significant negative impacts in both small (-\$0.55) and large (-\$0.36) markets, the effect for COMMUNITY NEWS quickly dissipates from -\$0.43 to -\$0.08 as the number of stations in the market increases. MULTICULTURALISM follows a similar trend to DIVERSITY OF OPINION, losing about 30 percent of its negative impact from small (-\$0.19) to large (-\$0.13) markets. ADVERTISING also follows a similar trend to DIVERSITY OF OPINION and MULTICULTURALISM losing about 40 percent of its positive impact from small (\$0.34) to large (\$0.20) markets.

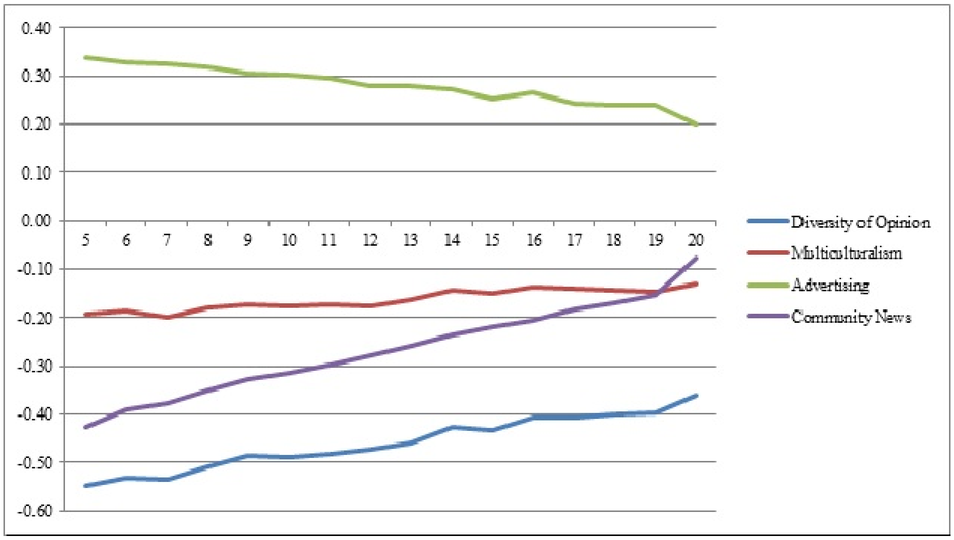
A final interesting observation is the potential tradeoff between the amount of diversity and

[21]The reported standard errors are calculated using a bootstrapping method. For example, in row one, we construct the benefit equation 7 for each respondent in markets with five TV stations. We then draw marginal utility values from the multivariate normal distribution implied by the mean and covariance parameters reported in column's eight and nine of Table 3.7. These values are used to evaluate equation 7 for each household respondent and to obtain an estimate of the mean consumer welfare effect per month. We run this simulation 500 times and report the mean and standard error of the sampling distribution for consumer welfare per month.

[22]There are 90,193,905 population households in markets from five to 20 TV stations. Total annual aggregate welfare for small markets is -\$45.07 million = (0.050x90,193,905)x12x-0.99. Total annual aggregate welfare for large markets is -\$15.51 million = (0.032x90,193,905)x12x-0.83.

[23]See CBS Corporation income statements at `http://ycharts.com/financials/CBS/income_statement/annual`.

Figure 3.1: Change in Average Consumer Welfare Per Month From a Change in Market Structure



NOTES. Vertical axis is dollars per month and horizontal axis is number of TV stations. The change in market structure is a one-unit reduction in the number of independent TV voices in the market, all other things held constant.

localism in news service, and the amount of space and time devoted to advertising. Consumers lose from the consolidation of two independent TV stations because there is less diversity of opinion, less coverage of multiculturalism issues and less community news, but they gain because there is less space and time devoted to advertising.[24] Specifically, columns three through six of Table 3.11 show that, on average, about 31 percent of the annual monthly losses to consumers from less diversity and localism in each market are offset by less exposure to advertising. This illustrates an important feature of the news service experience in our data; the first-order effects from consolidation are, potentially, not all bad for consumers. Nevertheless, consumers and policy makers should be concerned about the impacts from a "virtual merger" where TV stations combine their news operations with joint operating and marketing agreements without actually merging. Since a virtual merger is likely to result in less diversity and localism but not less advertising, the welfare reductions in Table 3.11 would be even more pronounced. For example, column twelve shows that if the virtual merger occurred in all markets, annual aggregate losses nationwide would be about \$992 billion.[25]

[24]The reduction in advertising does not mean that that the two merged firms will be worth less. Profits are expected to increase as a result of higher advertising rates and/or cost efficiencies in the production of news.

[25]The FCC use several measures of market structure when discussing ownership rules. For robustness, we examined how sensitive our results are to an alternative specification of the media supply equation 4 that controls for the

3.6 Conclusion

This study examined market structure and media diversity. A mixed logit model was used to estimate consumer demand for their local news service, described by the offerings from newspapers, radio, TV, the Internet, and Smartphone. The model captures both private and public good aspects of news service by including the amount of advertising in the household's full cost of consumption, and by characterizing service in terms of diversity of opinion in the reporting of information, coverage of multiculturalism issues, and the amount of information on community news and events. The empirical results show that the representative consumer values diversity in the reporting of news, more information on women and minorities, and more information on community news. Many consumers, however, distaste advertising, which likely reflects their consumption of general, all-purpose advertising from traditional media.

The demand estimates are used to conduct a simple policy experiment that calculates the impact on consumer welfare from a marginal decrease in the number of independent TV stations that lowers the amount of diversity, localism and advertising in the market. The prediction of non-price effects is appropriate for media markets, where some households make no direct payment for consumption, and appears to be novel in the simulated merger literature. Our results show that consumer welfare decreases following the change in media market structure, and that the losses are smaller in large markets. For example, small-market consumers lose \$45 million annually while large-market consumers lose \$13 million. If the change in market structure occurs in all markets, total losses would be about \$681 million.

We make no claims as to whether media ownership rules should be relaxed or tightened. We note that the estimated total losses of \$681 million approximates the extreme case of consolidation between two major national media players and, as such, is an upper-bound calculation. The large consumer losses in small TV markets relative to large markets is potentially important. The tradeoff between diversity and localism, and advertising, is also interesting because it highlights an additional benefit for consideration during the analysis of a media market merger. It also provides a new angle from which to assess the efficacy of media ownership rules.

number of daily newspapers in the market (NEWSPAPERS) and the number of radio stations (RADIO STATIONS). Estimates of the ordered probit model of media supply, and the estimates of the impacts on consumer welfare from a change in market structure, not reported here, are similar to those presented in Tables 3.10 and 3.11.

Bibliography

Adams, William James and Janet L. Yellen, "Commodity Bundling and the Burden of Monopoly," *The Quarterly Journal of Economics*, 1976, *90* (3), pp. 475–498.

Aghion, P. and P. Bolton, "Contracts as a Barrier to Entry.," *The American Economic Review*, 1987, *77*, 388–401.

Bernheim, D. and M. Whinston, "Exclusive Dealing.," *The Journal of Political Economy*, 1998, *106*, 64–103.

Berry, S. and J. Waldfogel, "Free entry and Social Inefficiency in Radio Broadcasting.," *The Rand Journal of Economics.*, 1999, *30*, 397–420.

_ , J. Levinsohn, and A. Pakes, "Automobile Prices in Market Equilibrium.," *Econometrica.*, 1995, *63*, 841–890.

Berry, Steven T. and Joel Waldfogel, "Mergers, Station Entry, and Programming Variety in Radio Broadcasting," Working Paper 7080, National Bureau of Economic Research 1999.

Bork, R., *The Antitrust Paradox.*, Basic Books, 1978.

Brant, M., *Join Together Forty Years of the Rock Music Festival.*, Backbeat Books, 2008.

Brown, Keith and Peter J Alexander, "Market structure, viewer welfare, and advertising rates in local broadcast television markets," *Economics Letters*, 2005, *86* (3), 331–337.

Brownstone, David and Kenneth Train, "Forecasting new product penetration with flexible substitution patterns," *Journal of Econometrics*, 1998, *89* (1), 109–129.

Chen, Yongmin and Michael H Riordan, "PROFITABILITY OF PRODUCT BUNDLING*," *International Economic Review*, 2013, pp. 35–57.

_ and Scott J Savage, "The effects of competition on the price for cable modem internet access," *The Review of Economics and Statistics*, 2011, *93* (1), 201–217.

Choi, Jay Pil, "Bundling New Products with Old to Signal Quality, with Application to the Sequencing of New Products," *International Journal of Industrial Organization*, 2003, *21* (8), 1179 – 1200.

Chu, Chenghuan Sean, "The effect of satellite entry on cable television prices and product quality," *The RAND Journal of Economics*, 2010, *41* (4), 730–764.

Connolly, Marie and Alan B. Krueger, "Rockonomics: The Economics of Popular Music," *Handbook of the Economics of Art and Culture*, 2006, *1*, 667–719.

Crawford, G, "Television station ownership structure and the quantity and quality of tv programming," *Federal Communications Commission Media Ownership Study*, 2007, (3).

Cunningham, Brendan M and Peter J Alexander, "A theory of broadcast media concentration and commercial advertising," *Journal of Public Economic Theory*, 2004, *6* (4), 557–575.

Domberger, Simon, "Sherr, Avrom,The Impact of Competition on Pricing and Quality of Legal Services," *International Review of Law and Economics*, 1989, *9*, 41–56.

Drushel, Bruce E, "The Telecommunications Act of 1996 and radio market structure," *Journal of Media Economics*, 1998, *11* (3), 3–20.

Economides, Nicholas, Katja Seim, and V Brian Viard, "Quantifying the benefits of entry into local phone service," *the RAND Journal of Economics*, 2008, *39* (3), 699–730.

FCC, "Government Furnished Information on Media Market Structure," *Media Bureau*, 2011.

Fort, Rodney and Jason Winfree, "Sports Really are Different: The Contest Success Function and the Supply of Talent," *Review of Industrial Organization*, 2009, *34*, 69–80.

Gentzkow, Matthew, "Valuing New Goods in a Model with Complementarity: Online Newspapers," *The American Economic Review*, 2007.

_ **and J Shapiro**, "What drives media slant? Evidence from US daily newspapers," *Econometrica*, 2013.

Goolsbee, Austan and Amil Petrin, "The consumer gains from direct broadcast satellites and the competition with cable TV," *Econometrica*, 2004, *72* (2), 351–381.

Greenstein, Shane and Feng Zhu, "Is Wikipedia Biased?," *The American Economic Review*, 2012, *102* (3), 343–348.

Groseclose, Tim and Jeffrey Milyo, "A measure of media bias," *The Quarterly Journal of Economics*, 2005, *120* (4), 1191–1237.

Hotelling, H., "Stability in Competition.," *Economic Journal*, 1929, *39*, 41–57.

Huber, Joel and Klaus Zwerina, "The importance of utility balance in efficient choice designs," *Journal of Marketing research*, 1996, pp. 307–317.

Imbens, Guido and J Wooldridge, "Control Function and Related Methods," *Whats New in Econometrics*, 2007.

Ivaldi, Marc and Frank Verboven, "Quantifying the effects from horizontal mergers in European competition policy," *International Journal of Industrial Organization*, 2005, *23* (9).

Jacobson, Robert and David A. Aaker, "The Strategic Role of Product Quality," *The Journal of Marketing*, 1987, *51* (4), pp. 31–44.

Knopper, S., "Attorney General Investigates Lollapalooza.," *Rolling Stone Magazine.*, June 2010.

Kot, G., "Lollapalooza one of many festivals with exclusivity clauses," `http://leisureblogs.chicagotribune.com/turn_it_up/2010/06/lollapalooza-one-of-many-festivals-with-exclusivity-clauses.html` June 2010.

Lafontaine, F. and M. Slade, "Exclusive Contracts and Vertical Restraints: Empirical Evidence and Public Policy.," *Handbook of Antitrust Economics, Paolo Buccirossi (ed.).*, 2008, pp. 391–414.

Lancaster, Kelvin, *Consumer Demand: A New Approach*, New York: Columbia University Press, 1971.

Liebowitz, S., "Will MP3 Downloads Annihilate the Record Industry? The Evidence So Far.," *Advances in the Study of Entrepreneurship, Innovation and Economic Growth*, 2004, *15*, 229–260.

Marvel, Howard P., "Exclusive Dealing.," *Journal of Law and Economics*, 1982, *25*, 1–25.

Matsa, David A., "Competition and Product Quality in the Supermarket Industry," *The Quarterly Journal of Economics*, 2011, *126* (3), 1539–1591.

Matsa, David A, "Competition and product quality in the supermarket industry," *The Quarterly Journal of Economics*, 2011, *126* (3), 1539–1591.

Mazzeo, M., "Product Choice and Oligopoly Market Structure.," *The Rand Journal of Economics*, 2002, *33*, 221–242.

Mazzeo, Michael J, "Competitive outcomes in product-differentiated oligopoly," *Review of Economics and Statistics*, 2002, *84* (4), 716–728.

_ , "Competition and service quality in the US airline industry," *Review of industrial Organization*, 2003, *22* (4), 275–296.

McAfee, R. Preston, John McMillan, and Michael D. Whinston, "Multiproduct Monopoly, Commodity Bundling, and Correlation of Values," *The Quarterly Journal of Economics*, 1989, *104* (2), pp. 371–383.

McFadden, Daniel, "Modelling the Choice of Residential Location," Cowles Foundation Discussion Papers 477, Cowles Foundation for Research in Economics, Yale University 1977.

McKelvey, Richard D and William Zavoina, "A statistical model for the analysis of ordinal level dependent variables," *Journal of Mathematical Sociology*, 1975, *4* (1), 103–120.

Milyo, Jeffrey, "The effects of cross-ownership on the local content and political slant of local television news," *FCC Report*, 2007, *7000029.*

Mortimer, J.H., C. Nosko, and A. Sorensen, "Supply responses to digital distribution: Recorded music and live performances," *Information Economics and Policy*, 2012.

Nevo, Aviv, "Mergers with differentiated products: The case of the ready-to-eat cereal industry," *The RAND Journal of Economics*, 2000, pp. 395–421.

Oberholzer-Gee, F. and K. Strumpf, "The Effect of File Sharing on Record Sales: An Empirical Analysis.," *Journal of Political Economy*, 2007, *115*, 1–42.

Olivares, Marcelo and Gérard P Cachon, "Competing retailers and inventory: An empirical investigation of General Motors' dealerships in isolated US markets," *Management Science*, 2009, *55* (9), 1586–1604.

Petrin, A., "Quantifying the Benefits of New Products: The Case of the Minivan," *The Journal of Political Economy*, 2002, *110* (4), 705–729.

Pinkse, Joris and Margaret E Slade, "Mergers, brand competition, and the price of a pint," *European Economic Review*, 2004, *48* (3), 617–643.

Posner, R., "The Next Step in the Antitrust Treatment of Restricted Distribution: Per Se Legality.," *University of Chicago Law Review*, 1981, *48*, 6–26.

Revelt, David and Kenneth Train, "Mixed logit with repeated choices: households' choices of appliance efficiency level," *Review of Economics and Statistics*, 1998, *80* (4), 647–657.

Rhee, Byong-Duk, "Consumer Heterogeneity and Strategic Quality Decisions," *Management Science*, 1996, *42* (2), pp. 157–172.

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*, April 2006, *49*, 29–62.

Rogers, R. and J. Woodbury, "Market Structure, Program Diversity, and Radio Audience Size.," *Contemporary Economic Policy.*, 1996, *14*.

Rojas, Christian., "The Competitive and Welfare Effects of Exclusive Agreements: Evidence from US Brewing.," *Working Paper: available in SSRN.*, 2011.

Sass, T., "The competitive effects of exclusive dealing: Evidence from the U.S. beer industry.," *International Journal of Industrial Organization.*, 2005, *23*, 203–225.

Savage, Scott J and Donald M Waldman, "Learning and fatigue during choice experiments: a comparison of online and mail survey modes," *Journal of Applied Econometrics*, 2008, *23* (3), 351–371.

Schaumans, Catherine and Frank Verboven, "Entry and competition in differentiated products markets," 2011.

Segal, I. and M. Whinston, "Naked Exclusion: Comment.," *American Economic Review.*, 2000, *90*, 296–309.

Shaked, A and J. Sutton, "Product Differentiation and Industrial Structure.," *Journal of Industrial Economics*, 1987, *36*, 131–146.

Siegelman, Peter and Joel Waldfogel, "Race and radio: Preference externalities, minority ownership, and the provision of programming to minorities," *Advances in Applied Microeconomics*, 2001, *10*, 73–107.

Simpson, J. and A. Wickelgren, "Naked Exclusion, Efficient Breach, and Downstream Competition.," *American Economic Review.*, 2007, *97*, 1305–1320.

Singh, Vishal and Ting Zhu, "Pricing and market concentration in oligopoly markets," *Marketing Science*, 2008, *27* (6), 1020–1035.

Slade, M., "Beer and the Tie: Did Divestiture of Brewer-Owned Public Houses Lead to Higher Beer Prices?.," *The Economic Journal*, 1998, *108*, 562–602.

Stigler, G.J., “A Note on Block Booking,” *The Organization of Industry*, 1968.

Waldfogel, Joel, “Bye, Bye, Miss American Pie? The Supply of New Recorded Music Since Napster,” Technical Report 16882, National Bureau of Economic Research March 2011.

Wolinsky, Asher, “Prices as Signals of Product Quality,” *The Review of Economic Studies*, 1983, *50* (4), 647–658.

Yan, Michael Zhaoxu and Philip M Napoli, “Market competition, station ownership, and local public affairs programming on broadcast television,” *Journal of communication*, 2006, *56* (4), 795–812.

Zenter, A., “Measuring the Effect of File Sharing on Music Purchases.,” *Journal of Law and Economics.*, 2006, *49*, 63–90.