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The Importance of Quality: How Music Festivals Achieved Commercial Success

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Abstract

Despite the existence of a number of famous American music festivals in the 20th century there was no major annual production until the early 2000s. This paper examines what characteristics are important to current commercially successful music festivals when making hiring decisions. This decision is similar to other industries such as professional athletics and online video services including Amazon Prime and Netflix, all forced to make input decisions that are suboptimal from a pure demand perspective because of a range of costs. A model of customer demand motivates the empirical analysis and provides an explanation for why festivals hire bands at varied levels of success and quality. 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 consumers, as well as what input substitutions must be made to establish profitability. Results show that music festivals are more likely to hire inexperienced bands of higher quality as inputs over experienced successful bands in order to take advantage of the lower costs, a practice which is likely extended to other industries.

Keywords: Input quality, product characteristics, music industry, entertainment industry, expectations, bundling

JEL Codes: L15, L82, D84

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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 also the possibility that the festival can cause an increase in demand for live music in that same area (Hiller, 2011). 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 (2001), and others that has explored empirical methods for estimating models of consumers with heterogeneous preferences and the impact of varied product characteristics. Mazzeo (2002), Chu (2010), and Matsa (2011) 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

[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.

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 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.

[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.

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.

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

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

cost are not always 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 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.

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.

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. As Hiller (2011) notes, 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

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

an album is a different 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.

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. 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} 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]

$$u_{likt}(q_{kt}) + u_{lint}(q_{mt-1}) \geq p_{it} \tag{1}$$

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:

$$\begin{gathered}\max_{q_{kt}, q_{nt}} \sum_{t=1}^{T} p_{it} - Fee_{ikt}(q_{kt}) - Fee_{int}(q_{mt}) \\ s.t.\ u_{likt}(q_{kt}) + u_{lint}(q_{nt-1}) = p_{it}\ \forall t\end{gathered} \tag{2}$$

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:

$$\frac{Fee'_{ik1}(q_{k1})}{Fee'_{in1}(q_{n1})} = \frac{u'_{lik1}(q_{k1})}{u'_{in2}(q_{n1})} \tag{3}$$

[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 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.

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.

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:

$$\begin{aligned}\pi^*_{ijt} =& Revenue^*_{ijt}(Experience_{jt}; Quality_{jt}; PastQuality_{jt}; Popularity_{jt}; PastPopularity_{jt}) \\ &- Fee^*_{ijt}(Experience_{jt}; Quality_{jt}; PastQuality_{jt}; Popularity_{jt}; PastPopularity_{jt}) + \epsilon_{it}\end{aligned} \tag{4}$$

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:

$$\begin{aligned}Revenue^*_{ijt} =& \gamma_1 PriorFests_{jt} + \gamma_2 PriorFestRank_{jt} + \gamma_3 LastToured_{jt} + Quality_{jt}\Theta \\ &+ Popularity_{jt}\Gamma + \epsilon_{it}\end{aligned} \tag{5}$$

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:

$$\begin{aligned}\pi^*_{jit} =& Fee^*_{ijt}(Experience_{jt}; Quality_{jt}; PastQuality_{jt}; Popularity_{jt}; PastPopularity_{jt}) \\ &- CostTouring^*_{jit} - OppCost_{jit} + \epsilon_{jt}\end{aligned} \tag{6}$$

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, $-j$:

$$\pi^*_{ijt} \geq \pi^*_{i-jt} \tag{7}$$

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

$$\pi^*_{jit} \geq 0 \tag{8}$$

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 6 can now be substituted into Equation 4, eliminating the fee paid to the band and providing an equilibrium for band j to be hired if the function in Equation 9 satisfies profit maximization:

$$\pi^*_{ijt} = Revenue_{ijt} - CostTouring_{jit} - OppCost_{jit} + \epsilon_{it} - \epsilon_{jt} \tag{9}$$

The hiring of any band to participate in a festival must satisfy Equation 7. The difference in profit of a band playing a festival versus any others in the sample not hired is now:

$$\begin{aligned}\pi^*_{ijt} - \pi^*_{i-jt} =& Revenue_{ijt} - CostTouring_{jit} - OppCost_{jit} - Revenue_{i-jt} \\ &+ CostTouring_{-jit} + OppCost_{-jit} + \epsilon_{jt} - \epsilon_{-jt}\end{aligned} \tag{10}$$

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.

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:

$$\begin{aligned} AveFestRank_{jit} =& \gamma_1 PriorFests_{jt} + \gamma_2 PriorFestRank_{jt} + \gamma_3 LastToured_{jt} \\ &+ Quality_{jt}\Theta + Popularity_{jt}\Gamma + \epsilon_{jt} \end{aligned} \tag{11}$$

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.

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 Appendix A.

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. 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

[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.

[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.

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 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.

[12] http://www.metacritic.com/about-metascores, Accessed 10/11/2011.

[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 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 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.

5.1 Summary Statistics

Information on the observed festivals through the sample years is available in Table 2. 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 3 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

[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.

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.

The sample has been limited in Table 4 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.

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.

6 Results

The model in Section 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 Tables 5-8. The marginal effects will be referenced in the text for ease of interpretation. The corresponding raw results can be found in Tables 15-18. 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 6.1, and then measured by how many quality ratings ($TotalRatings$) a band is included in in Section 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 9 - 12. 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.

6.1 Models using a Quality Indicator

Table 5 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

[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.

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 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 5 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]

6.2 Models using Total Inclusion in Quality Measures

Table 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 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 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

[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

25 percent in the year of that album, diminishing rapidly in following years.

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 7 and 8 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 8 than in the simpler *Rating* model in Table 7. 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 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.

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 9 and 10 provide the results for the model of Equation 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 9 and 10 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 9.

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

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 11 and 12, 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.

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.

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 13 and 14 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.

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.

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

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.

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.

References

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.

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

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.

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.

Hiller, Scott, "Exclusive Dealing and its Effects: The Impact of Large Music Festivals on Local Music Venues," *SSRN eLibrary*, 2011.

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

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

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

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.

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.

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

Petrin, Amil, "Quantifying the Benefits of New Products: The Case of the Minivan," Working Paper 8227, National Bureau of Economic Research April 2001.

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.

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

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.

Appendix A

Table 1: 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.

Table 2: 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 3: 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 4: 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

Table 5: Hiring Models with an Indicator for Quality - Marginal Effects

	(1)	(2)	(3)	(4)
	Fest	Fest	Fest	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)
Rating*TopAlbum				0.04
				(0.13)
Year FixedEffects	Yes	Yes	Yes	Yes
Band FixedEffects	Yes	Yes	Yes	Yes
Observations	19327	19327	19327	19327
Pseudo R^2	0.196	0.214	0.247	0.248

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 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)
Everfest*Rating					0.45*
					(0.14)
Year FixedEffects	Yes	Yes	Yes	Yes	Yes
Band FixedEffects	Yes	Yes	Yes	Yes	Yes
Observations	19327	19327	19327	19327	19327
Pseudo R^2	0.194	0.212	0.246	0.246	0.246

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 7: 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)
Rating*TopAlbum				0.049
				(0.16)
Year Fixed Effects	Yes	Yes	Yes	Yes
Band Fixed Effects	Yes	Yes	Yes	Yes
Observations	5705	5705	5705	5705
Pseudo R^2	0.229	0.258	0.317	0.317

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 8: 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
Pseudo R^2	0.228	0.258	0.318	0.318

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 9: 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 10: Prominence Models with Total Ratings Measuring Quality

	(1)	(2)	(3)
	AveFestRank	AveFestRank	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.

Table 11: 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 12: 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.

Table 13: Percentage Prominence Models with Simple Ratings Measuring Quality

	(1)	(2)	(3)
	PerRank	PerRank	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 14: 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.

Table 15: Hiring Models with an Indicator for Quality - Raw Results

	(1)	(2)	(3)	(4)
	Fest	Fest	Fest	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)

Table 16: 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)

Table 17: 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)

Table 18: 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)