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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

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, 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-

bined 9e-h the somewhat transient nature of touring bands, the music festival has an e ective monopoly on the local performance of the participating musicians. They can use this monopoly to force the consumer whose combined utility of performers is su ciently high to purchase the right to view all of the performances 9e-hin the festival in order to see the bands 9hich are of interest to her.

This stands in stark contrast to the standard musical performance where a venue provides one or two primary bands 9e-h a considerably lower ticket price.[5] In this respect the music festival acts much like the examples of pure bundling rms 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 rm may use a well known high quality product 9e-h a newly introduced product to encourage the new product's purchase. This di ers from my model in terms of music festivals using the new product as a cost e cient means of enhancing reputation, but the informational advantage of the rm is similar.

The inelastic supply means that festival producers cannot simply choose between inexhaustible quality di erentiated inputs. Instead, while the festival decides on whom to hire the band must also be in agreement 9e-h the festival regarding their fee, taking into consideration

unknown bands choosing quality of each band they hire rather than quantity. The consumer then buys the ticket if:[6]

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:

$$
\begin{aligned}
{}_{ijt} = {} & Revenue_{ijt}(Experience_{jt}; Quality_{jt}; PastQuality_{jt}; Popularity_{jt}; PastPopularity_{jt}) \\
& Fee_{ijt}(Experience_{jt}; Quality_{jt}; PastQuality_{jt}; Popularity_{jt}; PastPopularity_{jt}) + {}_{it}
\end{aligned} \tag{4}
$$

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:

$$
\begin{aligned}
Revenue_{ijt} = {} & {}_1 PriorFests_{jt} + {}_2 PriorFestRank_{jt} + {}_3 LastToured_{jt} + Quality_{jt} \\
& + Popularity_{jt} + {}_{it}
\end{aligned} \tag{5}
$$

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 pro t function, also not observed, is:

$$_{jit} = \mathrm{Fee}_{ijt}(\mathrm{Experience}_{jt}; \mathrm{Quality}_{jt}; \mathrm{PastQuality}_{jt}; \mathrm{Popularity}_{jt}; \mathrm{PastPopularity}_{jt})$$
$$\mathrm{CostTouring}$$

conditional xed e ects logit. The di erence in pro t between the chosen band and all others,

$ijt \quad i \quad jt >$

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 $q_1 > \ldots > q_n$, 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.

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[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.

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 has a de nitive probability increase of approximately 25 percent in the same year, but lagging variables included in column 4, only one is signi cant at the ve percent level.[17]

6.2 Models using Total Inclusion in Quality Measures

Table 6 presents the marginal e ects 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 rst national tour is signi cantly 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 rst time in the sample makes it di cult for a festival to evaluate their potential quality and t 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 e ect 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, Touringsqupo6t728(w)erienced95g 0 Td [ualit0 -17.6 -17.d [ualit0 -17.-279(a)-24.-279(a4(rating3391(b)-277

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 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 coe cient estimates then indicate that the given attribute increases a band's prominence or lineup \rank," while a positive coe cient predicts a decreasing e ect.

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 coe cients 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 signi cant and have a more substantial impact in both the rst 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 rst 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* coe cient having an e ect of only 3.7 in the same period in Table 9.

Con rming 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 e ects 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 e ect on reputation in ensuing periods, and hiring bands with well selling albums for their immediate impact on demand.

The e ects of some simple band characteristics on determining prominence have reversed

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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

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 hiring actors and establishing e ects budgets. These are several examples of possible industries which could be explained through similar models, but this list is by no means extensive.

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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 rst tour in the sample.
TourCosts	Indicator for a band not touring outside of a festival in a year.
FirstRating	Indicator for a rst 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

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

	(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 FixedE ects	Yes	Yes	Yes	Yes
Band FixedE ects	Yes	Yes	Yes	Yes
Observations	19327	19327	19327	19327
Pseudo R^2	0.196	0.214	0.247	0.248

Table 6: Hiring Models with Total Quality Inclusions - Marginal E ects

	(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)

Table 7: Hiring Models with an Indicator for Quality and Tour Indicators - Marginal E ects

	(1)	(2)	(3)	(4)
	Fest	Fest	Fest	Fest
Rating	0.147**	0.135**	0.171*	0.178*
	(0.06)	(0.05)	(0.07)	(0.07)

Table 8: Hiring Models with Total Quality Inclusions And Top Tour Indicators - ME

	(1)	(2)	(3)	(4)
	Fest	Fest	Fest	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
			Las49*50t-2	

(0.96.438* T93354t-2(0.96.4

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

Standard errors in parentheses
$p < 0:05$, $p < 0:01$, $p < 0:001$
The dependent variable, AveFestRank, is the average \rank" of all the festivals a band is in.

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	-17.14B22(-0.800)9 Td [( )]TJ/F30 8.9664 Tf 41.449 - ru17.146	

Table 13: Percentage Prominence Models with Simple Ratings Measuring Quality

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

Standard errors in parentheses
p < 0:05, p < 0:01, p < 0:001
The dependent variable, PerRank, is the average \rank" as a percentage of total festival slots available.

Table 14: Percentage Prominence Models with Total Ratings Measuring Quality

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

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

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)