# AN EMPIRICAL ANALYSIS OF THE FREQUENCY AND LOCATION OF CONCERTS IN THE DIGITAL AGE

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**Abstract**

As recorded music sales have dropped, live performances have become an important revenue source for artists. In this context, we study how the geographical distribution of concerts has evolved during the digital music era. Using data on more than 33,000 concerts in the United States from 2000 to 2011, we investigate how the distribution of concert locations has evolved over time. Our analysis shows that artists performed more concerts from 2000 to 2011, and that these concerts became more geographically dispersed during this period.



**Keywords:** Concert; Music industry; Long tail; Geographic distribution

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## 1. INTRODUCTION

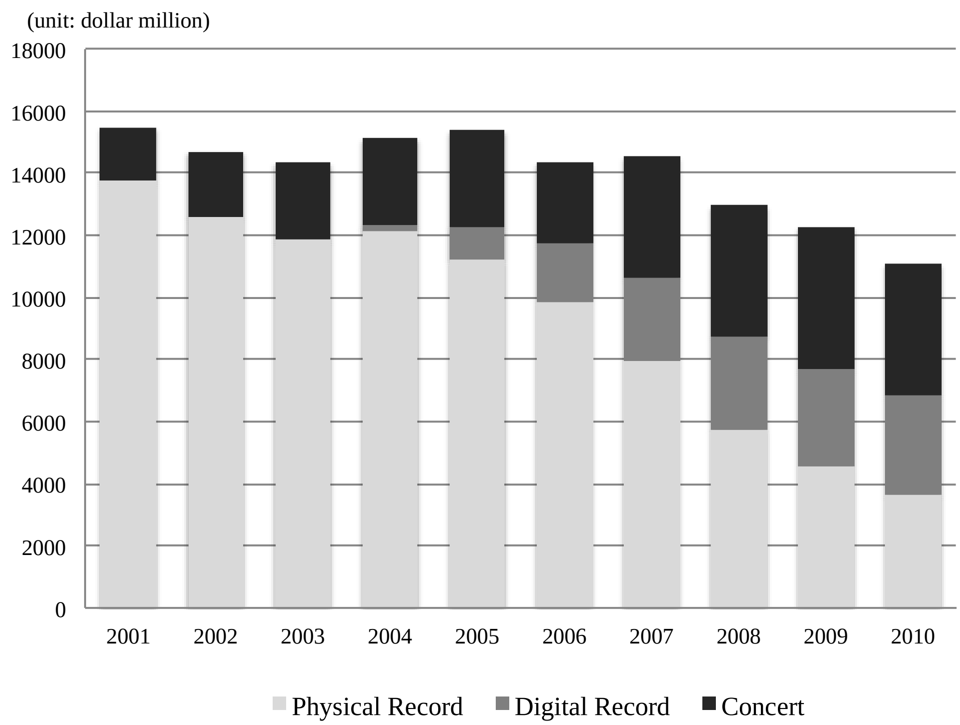
Traditional music industry business models have been altered due to advancements in information technology. One of the most notable, and for some, difficult changes is in income sources for artists. Music artists have traditionally generated income in two ways: royalties from recorded music sales and revenues from live performances.[1] In recent years, with the dramatic decline in recorded music sales, artists' income sources have significantly shifted from royalties on recorded music toward live performances (Krueger 2005). For example, the live music industry has become the largest music sector, outstripping recorded music in the United Kingdom in 2009, and increasing relative to recorded music in subsequent years (Frith 2007, Page and Carey 2009).

Figure 1 illustrates a sharp drop in income from U.S. music sales for the industry in the United States from 2001 through 2010. During this same time period, the size of the concert market rose from $1.75 billion (2001) to $4.25 billion (2010). The marked increase in concerts may be related to concert prices and/or the number of concerts. According to annual charts from *Pollstar*, a major trade magazine for the concert tour industry, the average ticket price of concerts by the top 100 artists in North America increased by 58% (from $42.2 in 2001 to $66.59 in 2009), while the consumer price index (CPI) increased by 14% during the same period.[2] In addition to this rise in concert

[1] Some songwriters generate additional income from music publishing fees.
[2] Similarly, according to Connolly and Krueger (2006), "From 1996 to 2003, for example, the average concert price increased by 82%, while the CPI increased by 17%." Note that the sales figures in Figure 1, however, are defined as prices of records and concert tickets that have not been adjusted for inflation.

ticket prices, there is also a possibility that artists gave more concerts, which has been understudied in the literature (Connolly and Krueger 2006).

**Figure 1. Music Industry Sales in the United States during 2001-2010**




Source: Recording Industry Association of America (RIAA), *Pollstar* magazine

In this paper we study how often artists have performed concerts in the post-file sharing age, placing special emphasis on the geographic distribution of concert locations. In other words, our analysis addresses the following questions: First, did artists perform more concerts as recording sales drops, and if so, why? Second, how, if at all, did concert locations evolve over the period?

We conduct empirical analyses by using a unique data set containing information on concert locations across time and artists. Specifically, we investigate the geographic distribution of over 33,000 concerts performed by 110 well-known artists from 2000 to 2011 in the United States. Our results suggest that artists in our sample performed an increasing number of concerts over the years studied and that concert locations trend toward a long tail distribution from 2000 to 2011. In other words, the proportion of concerts in relatively small cities tends to increase over time, implying that the potential audience in these regions would have a chance to attend a greater number of concerts given by artists.

We conjecture that this distinctive feature may be associated with demand- and/or supply-side drivers as they relate to the impact of the Internet. On the supply-side, artists may need to compensate for falling recording sales resulting from widespread file sharing, so they are likely to perform a larger number of concerts. On the demand-side, enhanced online communication channels may provide useful information and convenience for artists and concert promoters to find potential concerts in previously unexplored places.

Our paper complements, from a different angle, the existing literature regarding how the Internet affects the music industry. When the impact of file sharing is considered, the majority of previous studies have focused on the impact of file sharing on recorded music – a fraction of total music revenues. This study, however, adopts a broad view of the entire music market: first, by accounting for the complementary benefits of recorded music and concerts, and second, by analyzing artists' concert behaviors in the digital age. Examining how geographic concert distributions have evolved is not only important for the academic literature, but it also provides managerial implications for those working within the music industry — artists, music labels and concert promoters, who may seek additional opportunities to generate income in the digital age.

## 2. RELATED LITERATURE

Our work relates to two strands of the literature: the impact of piracy on sales of copyrighted goods, and market dynamics in the concert industry.

In the context of the impact of piracy on sales, from a theoretical perspective economists have studied two competing effects of digital piracy on copyright owners (Liebowitz 1985, Liebowitz 2008): the negative substitution effect of piracy and the potentially positive sampling effect of piracy. To explore these competing effects, empirical studies have examined the impact and consequence of digital piracy in a variety of different contexts (see Danaher et al. 2014 for a review of this literature). The vast majority of studies in this literature have documented a reduction in music sales associated with piracy (see for example Peitz and Waelbroeck (2004), Zentner (2005), and Liebowitz (2008) who examined the impact of Internet adoption on music sales, Zentner (2006), Rob and Waldfogel (2006, 2007), Hong (2013), and Michel (2006) who used survey data to analyze album and movie piracy, Danaher et al. (2010) who used direct observation of P2P activities to measure the impact of digital channel usage on piracy, and DeVany and Walls (2007) who used theatrical sales data to measure the impact of music piracy.

While the majority of empirical studies have found evidence that piracy harms sales of recordings, a few theoretical studies suggested positive aspects of file sharing (Peitz and Waeldbroeck 2006). In particular, Gayer and Shy (2006) identified certain conditions under which artists may benefit from music piracy by showing that the demand for live performances can rise with the increased popularity of artists generated by consumption of both legal and illegal copies.

Several studies have examined the market dynamics of the concert industry given the rise in live music consumption and the decline of recorded music sales (Holt 2010). For example, Connolly and Krueger (2006) show that the average price of concert tickets have increased with the transition from physical records to digital music. Krueger (2005) also argues that concerts are likely to be priced as single-market monopoly products than as a complementary good to recordings. Black et al. (2007) echoes this argument by demonstrating the rapid rise of ticket price and the inelastic demand of the top 100 tours in North America from 1997 to 2005.

As the concert market has grown, researchers have also studied the secondary ticket market (Leslie and Sorensen 2014, Bennett et al. 2015). Our paper extends the prior literature by analyzing the geographic distribution and frequency of concerts, highlighting the relationship between city size and the concentration of concerts.

Another stream of research focuses on an economic perspective of music consumption from recording and concert sales. Montoro-Pons and Cuadrado-Garcia (2011) analyze institutional change in the music industry, empirically demonstrating the positive network externality from the recorded music toward live concerts using survey data in Spain. Waldfogel (2012) documents that the distribution of songs at zero marginal costs would make concerts an increasingly important business model for the industry. Mortimer et al. (2012) extends this idea by empirically showing that while file sharing has a negative impact on the sales of music recordings, it also has a positive but differential impact on the demand for live concerts. Specifically, they show that the impact of file sharing is greater for lower-ranked artists than for top-ranked artists. Our study complements their results by examining the geographic distribution of concerts performed by top-ranked artists.

By studying the geographical distribution of concerts, our study is conceptually related to the Long Tail effect, a term coined by Anderson (2006).[3] The literature on this phenomenon examined the Long Tail phenomena by identifying demand side drivers (e.g., easy search tools and useful recommender systems to access niche products) of the media industry (Brynjolfsson et al. 2006, 2010). If cities are ordered by population, well-known artists may prefer to perform concerts in large cities because they may potentially attract a large number of audience in those cities, which may result in a Pareto distribution of concert locations. However, we conjecture that artists are likely to visit smaller cities as they give more concerts. If this phenomenon indeed occurs, the geographic distribution of concerts may tend shift toward the tail of the distribution, as seen in the long tail. In this regard, we focus on the following research question: which effect – Pareto or Long Tail – will prevail for concert location distribution in the digital age?

## 3. DATA

### 3.1 Data Collection

To address our research questions, we use historical concert information obtained from *Songkick.com*. These data include the artists' touring information — concert dates, and

[3] The Long Tail effect has been in dispute in recent academic research. Some researchers have found evidence that the Internet would also lead to a higher concentration of popular products in movie markets (Elberse and Oberholzer-Gee 2007), whereas Zentner et al. (2013) examined changes in video rental market sales as consumers moved from offline to online markets and suggested that consumers are more likely to rent niche titles in the online channel than in the offline channel.

concert locations. *Songkick.com* is known for offering rich information on live music events and has accumulated information on past concerts using an index of 135 different ticket vendors, venue websites, and local newspapers. To construct a data set of well-known artists, we use the year-end chart of the top 100 North American tours between 2000 and 2011 provided by *Pollstar Magazine*. The ranking chart is tabulated based on each artist's gross concert revenues for that year. The final data set between 2000 and 2011 includes 33,471 concerts in the United States.[4]

It is worth noting that the artist list of the ranking chart is different year by year, because it is common that artists do not tour every year. For this reason, we alternatively construct a data set using the ranking chart of the beginning year (the year 2000) of our study period by which we track the frequency and the location of concerts performed by the fixed group of artists shown in 2000. This approach will be addressed in Section 4.2.

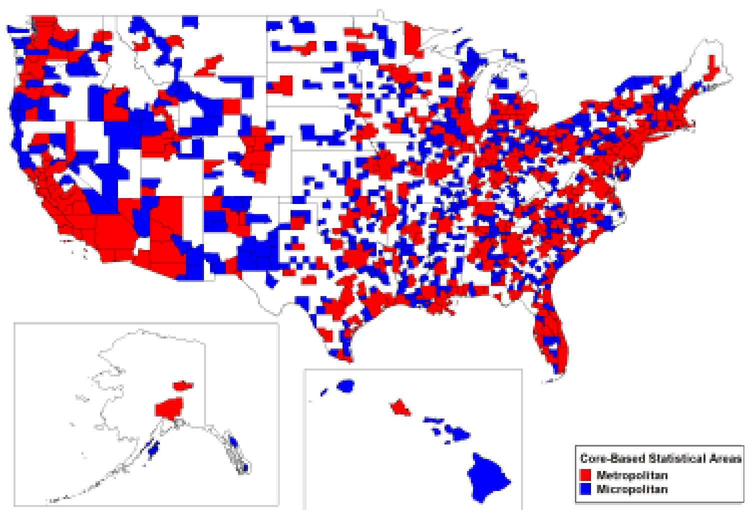
We then match each concert location to its corresponding Core-based Statistical Area, hereafter CBSA. We use this geographic standard for two reasons. First, our research strategy requires us to establish an appropriate level of geographic divisions for concerts. For our purposes, zip code-level descriptions seem too specific, while state-level descriptions seem too broad. The Federal Office of Management and Budget (OMB) defines 942 CBSAs within the United States, with 366 of these CBSAs being classified as metropolitan areas (MSAs) having a population greater than 50,000, as shown in Figure 2. We account for these 366 MSAs, and they are ordered by population size in this study.[5] Second and more importantly, residents of each CBSA are socio-economically

[4] Some examples are Bob Dylan, Bon Jovi, Dave Matthews Band, Elton John, Madonna, Mariah Carey, Pearl Jam, Roger Waters, Santana, Shakira, and U2. Our sample also includes recent superstar artists such as Norah Jones, Jason Mraz, Beyonce and Taylor Swift who began their careers after 2000.

[5] The population size of the metropolitan areas shows a wide variation from nearly 20 millions in New York City area to 55,000 in Carlson City, NV.

tied to the urban center by definition provided by the OMB, and this fact may indicate that people in the same CBSA would tend to share infrastructure and facilities in close proximity. For instance, the New York City CBSA includes 24 counties spread over three states (New York, New Jersey, and Pennsylvania), which indicates that many residents' daily routines in the CBSA occur within New York City proper. In other words, residents in this particular CBSA may also be regarded as potential audience of concerts held in New York City or other cities in the CBSA.

**Figure 2. The Core Based Statistical Areas of the United States**




Source: US Census Bureau

### 3.2 Descriptive Evidence

Table 1 presents descriptive statistics on the number of concerts by year. It tends to increase over our study period, but we also see a drop in the number of concerts after 2008, which may be due to the U.S. financial crisis. We are interested in studying artists' concert location choices over the region. Note that a higher (lower) rank indicates a greater (smaller) population in a CBSA. Based on the rank of each CBSA by population, we present the distribution of the cumulative number of concerts at various cutoff points for two consecutive years. Table 2 reports this initial check of the dynamics of the concert distributions.

**Table 1. Descriptive Statistics on Concert Tours for Artists**

| Year | Number of Artists | Total Number of Concerts | Concerts/Artist |
|---|---|---|---|
| 2000 | 100 | 2,644 | 26.44 |
| 2001 | 100 | 2,099 | 20.99 |
| 2002 | 100 | 2,594 | 25.94 |
| 2003 | 100 | 2,812 | 28.12 |
| 2004 | 100 | 2,646 | 26.46 |
| 2005 | 100 | 2,711 | 27.11 |
| 2006 | 100 | 2,416 | 24.16 |
| 2007 | 100 | 2,669 | 26.69 |
| 2008 | 100 | 3,733 | 37.33 |
| 2009 | 100 | 3,053 | 30.53 |
| 2010 | 100 | 3,166 | 31.66 |
| 2011 | 100 | 2,928 | 29.28 |
| Mean/year | 100 | 2,789 | 27.89 |

As can be seen of the table, the cumulative ratio of concerts tends to decline at all the cutoff points throughout our study period, indicating that the ratio of large concert regions shows a decreasing trend. In particular, the ratio of the top 5 CBSAs (New York City, Los Angeles, Chicago, Dallas, and Philadelphia) to all concerts in a given timeframe declined from 24.25% to 19.21% over the study period.

**Table 2. Distribution of the Cumulative Number of Concerts for a Two-Year Period**

| CBSA rank | 2000-2001 | 2002-2003 | 2004-2005 | 2006-2007 | 2008-2009 | 2010-2011 |
|---|---|---|---|---|---|---|
| Top 5 | 24.25% | 21.77% | 21.90% | 21.42% | 20.34% | 19.21% |
| Top 10 | 35.88% | 32.97% | 32.10% | 31.54% | 30.79% | 28.96% |
| Top 20 | 52.39% | 49.41% | 47.99% | 47.83% | 46.91% | 44.80% |
| Top 50 | 79.59% | 76.02% | 74.36% | 74.34% | 74.65% | 72.12% |
| Top 100 | 92.59% | 90.39% | 89.46% | 89.21% | 90.20% | 87.56% |

## 4. ESTIMATION AND RESULTS

In this section, we delve more deeply into the empirical properties of geographic concert distribution to demonstrate the observable implications of the dynamics discussed above. We begin our analysis by presenting the trends of the rank-size relationship. We then replicate the estimation using the data of the fixed group of artists who were shown in the chart of the year 2000.

### 4.1 Rank-Size Relationship

While we showed a declining trend of concert shares in the top ranked CBSAs in Table 2, this measure alone does not allow us to conclude whether such a difference is statistically significant (see Brynjolfsson et al. 2010). We thus fit the concert and rank data to the log-linear relationship and compare the resulting coefficients to examine whether the concentration of the distribution changes. Following Brynjolfsson et al. (2010), we use a log-linear relationship:

$$\log(concert_{it}) = \beta_0 + \beta_1 \log(rank_{it}) + \beta_2 \log(rank_{it}) \times trend + \beta_3 trend + \varepsilon_{it}, \quad (1)$$

where $i$ and $t$ denote CBSA and year, respectively. $concert_{it}$ denotes the number of concerts in CBSA $i$ in year $t$. We then rank the CBSAs by the number of concerts in year $t$, as $rank_{it}$. $trend$ is a sequential variable from 1 to 12 representing the time trend of years from 2000 to 2011.

Given our log-log specification, $\beta_1$ measures how quickly the proportion of concerts in CBSA $i$ goes down as the rank increases. $\beta_2$ indicates the coefficient estimate of the interaction terms between $\log(\mathrm{rank_{it}})$ and $\mathrm{trend}$, so this coefficient measures the change in the mean level of the slope as time progresses. If the distribution suggests a Long Tail effect (or is less concentrated for large cities), then $\beta_2$ would have a positive value, indicating that the estimated fitted line has become flatter (Brynjolfsson et al. 2010). To see differential trends, we have several cutoff points based on the CBSA rank.

Table 3 reports the results from this specification. When we include all CBSAs in the estimation in Column (1), the coefficient estimate for the interaction term is not statistically significant. However, when we account for only the top 20 CBSAs in Column (2), the estimated coefficient of the interaction term is positive and statistically significant at 5% level, indicating that the slope of the rank-size log-linear relationship tends to be flatter over time. These findings indicate that the distribution of concert locations has tended to disperse toward smaller regions within the Top 20 CBSAs.

Results in Columns (3) through (5) are consistent with this result. In other words, the geographical distribution of concerts for artists in our sample has tended to follow a Long Tail trend over time, at least for the top 200 CBSAs that account for approximately 234 million (75%) of the entire U.S. population. However, the coefficient estimated for the interaction term turns out not to be significant when even smaller CBSAs are considered, as in Columns (1) and (6). This observation seems to be reasonable because well-known artists, at least in our sample, are less likely to visit very small towns when they increase the number of concerts on their tours.

**Table 3. Regression of Rank-Size Relationship**

| DV:log(concert) | (1) All | (2) Top 20 | (3) Top 50 | (4) Top 100 | (5) Top 200 | (6) Top 300 |
|---|---|---|---|---|---|---|
| log(rank) | -1.284*** | -0.586*** | -0.698*** | -0.957*** | -1.248*** | -1.285*** |
| | (0.034) | (0.036) | (0.020) | (0.029) | (0.035) | (0.034) |
| log(rank)×trend | 0.001 | 0.007** | 0.011*** | 0.012*** | 0.014*** | 0.001 |
| | (0.005) | (0.003) | (0.002) | (0.004) | (0.005) | (0.005) |
| trend | 0.027 | -0.003 | -0.011 | -0.013 | -0.018 | 0.027 |
| | (0.022) | (0.011) | (0.007) | (0.014) | (0.021) | (0.022) |
| constant | 7.123*** | 5.244*** | 5.466*** | 6.099*** | 7.003*** | 7.125*** |
| | (0.162) | (0.082) | (0.060) | (0.109) | (0.159) | (0.162) |
| Observations | 3,146 | 240 | 600 | 1,200 | 2,400 | 3,142 |
| Adjusted R-squared | 0.907 | 0.860 | 0.896 | 0.890 | 0.898 | 0.905 |

Standard errors are indicated in parentheses: * significant at 10%; ** significant at 5%; and *** significant at 1%.

### 4.2 Additional Analysis with a Fixed Group of Artist

In Section 4.1, we used the concert data of artists who were listed on the year-end chart of the top 100 North American tours between 2000 and 2011. Using this data set, artists naturally vary year by year according to artists' touring plans. In this respect, one may wonder if the frequency and the location of concerts performed by a particular artist indeed change over time. To address this problem, we construct an additional data set of the fixed group of artists who were listed in the ranking chart of the beginning year (the year 2000) of our study period. This approach may supplement our main analysis presented in Section 4.1 by examining how each artist changed concert behaviors as time progresses.

Table 4 presents the number of active artists, the total number of concerts, and the number of concerts per artist each year. As can be seen, the total number of concerts and the number of concerts per artist tend to increase over our study period. A computed correlation coefficient between the $trend$ variable and the total number of concerts is

0.73, and the correlation coefficient between the *trend* variable and the number of concerts per artist is 0.69. Both correlation coefficients are statistically significant at 5% level.

**Table 4. Concert Tours of the Fixed Group of Artists**

| Year | Active Number of Artists | Total Number of Concerts | Concerts/Active Artist |
|---|---|---|---|
| 2000 | 100 | 2,644 | 26.44 |
| 2001 | 70 | 1,790 | 25.57 |
| 2002 | 76 | 2,311 | 30.26 |
| 2003 | 84 | 2,595 | 31.02 |
| 2004 | 81 | 2,269 | 28.04 |
| 2005 | 78 | 2,299 | 29.41 |
| 2006 | 83 | 2,191 | 26.48 |
| 2007 | 76 | 2,045 | 26.77 |
| 2008 | 85 | 3,070 | 35.93 |
| 2009 | 81 | 2,835 | 35.04 |
| 2010 | 79 | 2,979 | 37.67 |
| 2011 | 85 | 2,949 | 34.88 |
| Mean/year | 82 | 2,499 | 30.63 |

We then replicate a series of estimations that we did in Section 4.1 using the data set of the fixed group of artists. The results are presented in Table 5, indicating that estimated coefficients are very close to the corresponding outcomes in Table 3. In other words, artists who did successful tours in the year 2000 are likely to perform their concerts in more dispersed places in following years. As a result, this supplemental approach would enhance the validity of our main results.

**Table 5. Regression of Rank-Size Relationship (Artist-level Fixed Effect)**

| DV:log(concert) | (1) All | (2) Top 20 | (3) Top 50 | (4) Top 100 | (5) Top 200 | (6) Top 300 |
|---|---|---|---|---|---|---|
| log(rank) | -1.268*** | -0.574*** | -0.693*** | -0.951*** | -1.237*** | -1.268*** |
| | (0.034) | (0.026) | (0.018) | (0.029) | (0.035) | (0.034) |
| log(rank)×trend | 0.001 | 0.006* | 0.011*** | 0.012*** | 0.013*** | 0.001 |
| | (0.005) | (0.003) | (0.002) | (0.004) | (0.005) | (0.005) |
| trend | 0.028 | -0.000 | -0.010 | -0.012 | -0.016 | 0.027 |
| | (0.022) | (0.011) | (0.007) | (0.014) | (0.021) | (0.022) |
| constant | 7.019*** | 5.164*** | 5.396*** | 6.029*** | 6.917*** | 7.020*** |
| | (0.160) | (0.079) | (0.058) | (0.109) | (0.158) | (0.160) |
| Observations | 3,123 | 240 | 600 | 1,200 | 2,400 | 3,120 |
| Adjusted R-squared | 0.907 | 0.864 | 0.896 | 0.889 | 0.896 | 0.907 |

Standard errors are indicated in parentheses: * significant at 10%; ** significant at 5%; and *** significant at 1%.

As a further robustness check, we replace $trend$ variable to a dummy variable, $secondhalf_t$, in Equation (7), because the length of our study period is relatively long. $secondhalf_t$ is one if the year $t$ is from 2006 to 2011, and the variable becomes to be zero if the year $t$ is from 2000 to 2005. By replacing the $trend$ variable to $secondhalf_t$, the estimated coefficient for the interaction term, $\log(rank_{it}) \times secondhalf_t$, measures the change in the mean level of the slope between the two periods, 2000-2005 and 2006-2011. Results are reported in Appendix, and our findings from this alternative approach are indeed in line with main results in Sections 4.1 and 4.2.

## 5. DISCUSSION AND CONCLUSIONS

In this study, we examined how the geographic distribution of concert has evolved with the decline in music sales post-2000. Our paper provides empirical evidence of the existence of a long tail effect in music concerts in the digital age. The original definition of the long tail effect and empirical studies that followed have focused on the demand side (i.e., niches will constitute a larger proportion of demand on the Internet). Our work reverses the lens of analysis, showing that geographical concert location may also follow a long tail distribution. Our primary finding is that, although artists performed an increasing number of concerts throughout our study period, the degree of concentration in major U.S. cities declined over time for artists in our sample. In this respect, our finding indicates that potential audiences (particularly, those living in relatively small cities) have an increased number and variety of concert options. It is worth noting that this finding does not mean that citizens in the large cities have fewer chances to attend concerts due to the increasing proportion of concerts in the small cities. Rather, our findings suggest that the absolute number of concerts has tended to increase in all of the regions studied, but the relative growth in the small regions has been more noticeable.

In summary, from the perspective of the supply-side of the concert market, our study provides evidence that the distribution of concert locations tended to be dispersed in the digital age as well-known artists in our sample have performed a greater number of concerts. Future work may wish to extend our analysis by analyzing the factors associated with changing trends in concert locations, accounting for changes the demand-side of the concert market. Either present or potential concertgoers may obtain more information about artists and upcoming tours in their town by using online search tools with lower costs. Not only can they currently book a ticket through online channels[6] (e.g., Ticketmaster.com), but a variety of more direct interactions and communications with artists or other fans may also lead to a higher likelihood of fans attending concerts. According to Brynjolfsson et al. (2010), information available to consumers regarding

[6] For example, by using primary and secondary market concert sales data, Leslie and Sorensen (2010) argue that large decreases in transactions costs arising from the use of online outlets for ticket resale would lead to significant increases in social efficiency.

both niche and popular products are changing due to search tools, recommender systems, and social networks (e.g., Twitter, Facebook and YouTube).

Naturally our study is not without limitations. Due to the limited data available, we analyzed only the number of concerts played by artists. Future work could use data regarding concert ticket prices and/or the number of attendees per concert to provide more detail on this effect. Specifically, looking at market dynamics across regions and artists' popularity are promising future studies in our context. For example, there could be a possible crowding out effect toward small local bands as well-known artists perform more concerts in smaller regions. In this context, artists and promoters may have different strategies to maximize their profits. Another interesting approach for future research would be comparing outcomes for artists who proactively utilized social media versus artists who did not in the period immediately after the emergence of social networking sites.

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# APPENDIX

## Table A1. Regression of Rank-Size Relationship

| DV:log(concert) | (1) All | (2) Top 20 | (3) Top 50 | (4) Top 100 | (5) Top 200 | (6) Top 300 |
|---|---|---|---|---|---|---|
| log(rank) | -1.272*** | -0.559*** | -0.661*** | -0.911*** | -1.186*** | -1.272*** |
| | (0.022) | (0.021) | (0.014) | (0.019) | (0.023) | (0.022) |
| log(rank)×secondhalf | 0.001 | 0.040** | 0.072*** | 0.068** | 0.057* | 0.002 |
| | (0.032) | (0.018) | (0.019) | (0.027) | (0.033) | (0.032) |
| secondhalf | 0.164 | -0.017 | -0.082 | -0.067 | -0.033 | 0.163 |
| | (0.155) | (0.074) | (0.057) | (0.102) | (0.147) | (0.156) |
| constant | 7.200*** | 5.235*** | 5.433*** | 6.048*** | 6.900*** | 7.200*** |
| | (0.106) | (0.050) | (0.041) | (0.074) | (0.105) | (0.106) |
| Observations | 3,146 | 240 | 600 | 1,200 | 2,400 | 3,142 |
| Adjusted R-squared | 0.904 | 0.856 | 0.891 | 0.884 | 0.891 | 0.904 |

Standard errors are indicated in parentheses: * significant at 10%; ** significant at 5%; and *** significant at 1%.

## Table A2. Regression of Rank-Size Relationship (Artist-level Fixed Effect)

| DV:log(concert) | (1) All | (2) Top 20 | (3) Top 50 | (4) Top 100 | (5) Top 200 | (6) Top 300 |
|---|---|---|---|---|---|---|
| log(rank) | -1.255*** | -0.549*** | -0.655*** | -0.905*** | -1.176*** | -1.255*** |
| | (0.022) | (0.036) | (0.014) | (0.020) | (0.023) | (0.022) |
| log(rank)× secondhalf | -0.002 | 0.030 | 0.066*** | 0.064** | 0.047* | -0.001 |
| | (0.032) | (0.030) | (0.018) | (0.027) | (0.023) | (0.032) |
| secondhalf | 0.166 | 0.003 | -0.071 | -0.059 | -0.008 | 0.165 |
| | (0.153) | (0.069) | (0.055) | (0.102) | (0.147) | (0.153) |
| constant | 7.098*** | 5.160*** | 5.367*** | 5.980*** | 6.819*** | 7.098** |
| | (0.105) | (0.046) | (0.041) | (0.075) | (0.104) | (0.105) |
| Observations | 3,123 | 240 | 600 | 1,200 | 2,400 | 3,120 |
| Adjusted R-squared | 0.903 | 0.859 | 0.889 | 0.882 | 0.888 | 0.903 |

Standard errors are indicated in parentheses: * significant at 10%; ** significant at 5%; and *** significant at 1%.