Exploring spatial variations of US rock music concerts in relation to population demographics and leisure and hospitality industry

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ABSTRACT
Rock music is an integral part of American culture. This paper presents a study of sensing and analysing over 57,000 rock music live performances between 2007 and 2017. Spatial traces of 575 rock music artists performing in concerts nationwide were collected from a major music streaming platform Spotify. Location-based concert data were analysed to explore economic and geographic factors linked to the landscape of rock music live performance and to reveal the importance of population demographics and leisure and hospitality (LH) economics to the culture and music industries from a spatial aspect. Over 90% of rock concerts between 2007 and 2017 were found in 250 counties. The aim of the study is to specify and develop a model that reasonably accounts for spatial heterogeneity present in the concert data. By regressing rock concert data against demographic data and LH establishment data, ordinary least squares (OLS) models were better fitted in metropolitan counties than non-metropolitan counties. Spatial dynamics of concerts were revealed by local R² values and the obtained structure in the form of spatial heterogeneity was then explained using geographically weighted regression (GWR) models. High population density and LH services in industry-leading cities such as New York City, Los Angeles, Chicago and Houston exhibit advantages in explaining rock concert distributions. Findings from the models reflect the live music industry’s interrelationships to the LH industry and suggest LH services being essential considerations in selecting concert destinations for rock musicians.

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1. Introduction

Music plays an essential role in the culture, economy, and technological innovations of modern society (Earl 2001; Connolly and Krueger 2006; Florida and Jackson 2010; O’meara and Tretter 2013; van der Hoeven and Hitters 2019). The music activity is a part of our social intercourse and understanding ourselves through music has been socially recognized (Frith 2007). Many musical findings have been contextualized with socio-cultural importance (O’Regan 2013). For instance, (Stokes 2004) believed that music is an indicator of social processes and implies forms of cultural interactions. Acting as a catalyst for regional development by attracting investments and providing employment to a significant proportion of the population reflects the economic importance of music (Kong 1995). The music industry has a mutually beneficial relationship with technology that changes the structure of the music industry and promotes technological advances (Hracs 2012). Understanding how music is valued requires examinations of musical practices such as live performance in the context of social and technological changes (Holt 2010).

Rock music plays a significant part in American culture and greatly influences many other music genres (Ulmer 2015). As rock music performance is different from other performances in terms of the social and physical environment, more research is needed to understand its uniqueness (King 2017).

The live music sector, especially concerts, is undergoing a rapid expansion (Cameron 2016). The concert business has been a long-standing theme in the study of music and concert trends were analysed by investigating economic, social and cultural factors in order to explore the relationship between production and consumption and to understand the whole music industry (Earl 2001; Kong 1995; Black, Fox, and Kochanowski 2007; Decrop and Derbaix 2014; Johansson and Bell 2014). For instance, the age of a population was found with significant effects on the live-music business (Conner 2015). Additionally, (Deichmann 2014) believed that the music performance site choosing relates to cultural proximity. From a musician’s perspective, a concert is the main income source and a communication process with audiences (Hogg and Banister 2000; Connolly and Krueger...
Although websites, such as U2.com, have provided access to streaming and a detailed data set of concerts’ locations, this information is not always available and has not been used for the purpose of studying the relationship of geographies and the decision-making process of artists (Gao, 2015; Lashua, Spracklen, and Long 2014). Concert data represents a highly valuable proxy for describing the dynamics of the live music industry (Connolly and Krueger 2014; Papies and van Heerde 2017). By analysing concert data, companies can make decisions on whether or not the musician visits a site among a set of candidate locations to determine a profit-maximizing tour (Freeman, Keskin, and Çapar 2018). However, there are still rare discussions devoted to examining determinants of the demand for leisure, entertainment and hospitality services in relation to live music performance.

Studying geographies of the performing arts has offered a way of capturing the interconnectedness of different spatialities of the performing arts (Rogers 2018). There is a strong connection between music and geography both historically and contemporarily (Hudson 2006). A growing body of geographical literature is interested in the ‘spatial’ in music studies (Lashua, Spracklen, and Long 2014). The importance of studying the geography of music is increasingly recognized in music studies as it provides the fundamental geographic context to conceptualizing the relationship between music and place in a more extensive scope (Florida, Mellander, and Stolarick 2010). Analysing music geography using concert data has long been a valuable resource for the music investigative process of musician activities (O’meara and Tretter 2013). For instance, a map of U2’s touring circuit was generated in order to understand their performance location selections (Deichmann 2014). Geographic Information Systems (GIS) mapping technology was also used to create musical landscapes through spatial and historical mapping of live venues (Cohen 2012). (Shobe and Banis 2010) suggested that the combined use of geography and music is of usefulness and importance in researching cultural geography. Although studies of music from the geographic perspective have been flourishing in recent years, the use of geospatial science beyond recording spatial location and mapping concerts remains rare.

Most music research focusing on concert studies relies upon reports, surveys, interviews and musician’s websites, which allow researchers to identify characteristics of live music performance (Black, Fox, and Kochanowski 2007; McCarter 2012; O’meara and Tretter 2013; van der Hoeven and Hitters 2019). However, the main disadvantage of this method is that it only gives access to a small percent sampling of musicians and it took a long time to collect the data. Due to data availability, integrity, and consistency restrictions, it is almost impossible for studies to make a deep analysis from large spatial and temporal scales (Gao 2015). In recent years, various Internet technologies such as web services have been identified as valuable alternatives to lengthy and costly information sharing and musicians can easily release their records to promote their live music (Decrop and Derbaix 2014; Galuszka and Brzozowska 2017). The music streaming service has positively affected live music by providing new business models for musicians and the music industry (Nguyen, Dejean, and Moreau 2014). In the context of emerging Internet content and web service providers, the music streaming platform provides a powerful aid to the analysis and understanding of the music dynamics. In the past few years, music streaming platforms are the biggest growth driver and revenue contribution to the US music industry (Friedlander 2018). Spotify has emerged as one of the leading music streaming platforms with more than a hundred million active monthly users (Vonderau 2019). By collecting concert information using the official Spotify application programming interface (API), analysts can access a much larger dataset with fine spatio-temporal resolution and continuity, which allows for a more detailed analysis of the data at municipal, regional, and national scales.

Previously, several methods have been developed to account for the musician’s selection of the intended location of the concert. Simple descriptive and multivariate analyses are the most commonly used modelling techniques in the exploratory context. For instance, a descriptive analysis of U2’s worldwide tour was used to identify the significant role of market factors in the selection of their performance destinations (Deichmann 2014). Moreover, (van der Hoeven and Hitters 2019) also applied a qualitative content analysis of live music reports to understand live music concerts’ social and cultural value. The correlational analysis has also been used to identify common patterns of regional concert destinations, which assumes parametric stability in the joint relationship of variables and destination selection (Johansson and Bell 2014). A combination of correlational analysis and regression analysis has been used to examine the effects of economies on the geography of music (Florida, Mellander, and Stolarick 2010). However, the real-world geographic data does not always meet the assumption that joint relationships are stationary, also known as the stationarity assumption (Jiang and Shekhar 2017). The spatial non-stationarity can bias the estimates of model parameters in regression analyses when traditional regression methods are used. Discussions of explaining spatial non-stationarity in spatial data when modelling concert data as a function of explanatory variables have often been missed from the music study. Using the geographically weighted regression (GWR) method, local regression models can be
generated to address inconsistent relationships between response and explanatory variables for spatial data (Holt and Lo 2008; Light and Harris 2012).

A variety of different contextual characteristics such as demographic, social, cultural, economic, linguistic and other factors are critical in analysing the evolution of the music market (Liu, Hu, and Schedl 2018). Demographic factors have drawn the attention of city researchers and local governments to facilitate their understanding of live music benefits to urban development (van der Hoeven and Hitters 2019). The size of the music market was found to be related to the magnitude of the population (Moon, Barnett, and Lim 2010; Johansson and Bell 2014). The level of educational attainment can influence the demand for concert attendance (Toma and Meads 2007; Willekens and Daenekindt 2020). Language plays a significant role in the pricing of concerts and is influencing the international music market (Moon, Barnett, and Lim 2010; Decrop and Derbaix 2014). Economic determinants such as consumer occupational status and income determined a large share of concert revenues (Favaro and Frateschi 2007; Toma and Meads 2007; Deichmann 2014). Gender difference is important for managing and marketing music events (Kruger and Saayman 2015). For instance, (Palma-Martos, Cuadrado-Garcia, and Montoro-Pons 2021) reveal significant differences arising between men and women in terms of music consumption and preferences. Previous literature has shown that a variety of demographic variables were employed in revealing live music market development; however, most of these analyses were conducted investigating predictions of concert revenues or attendances, the spatial changes of concert distributions were seldom analysed.

The leisure and hospitality (LH) industry contributes to a large portion of the US economy (Tan 2012). For instance, the LH industry shows profound socioeconomic impacts on labour markets, workforce and employment (Laituri et al. 2021). As the importance of the LH industry is continually growing, a diverse range of service-related and creative industries associated with leisure, entertainment, hospitality and tourism has drawn the attention of cultural-economic geographers. For instance, the tourist industry in many places is economically dependent on musical events (Bracalente et al. 2011; Frey 1994). Also, music festivals cater to concertgoers from outside the local area visiting a city and enhancing the region’s travel economy (Bernick and Boo 2013; Henke 2005). While LH has recently been widely used to describe commercial activities, they rarely attract the attention of music researchers. The development of music-driven economy industries is vital to the future elaboration of culture-based policies of regional and local developments. Despite the immense economic and social impact of LH industry, few studies have explored and uncovered the linkage of music to industries such as leisure, entertainment, hospitality and tourism and what they mean to the economics of culture and music industries.

Over the past decade, there have been studies that viewed music through a geographical lens. Traditionally, the concert data analysis was limited to qualitative analysis for most studies. Relatively little of this recent work has taken an approach that considered spatial heterogeneity. Moreover, drawing on previous work by (Freeman, Keskin, and Çapar 2018), it was believed that a combination of various factors contributed to the planning and organizing of a successful concert. However, factors have not been sufficiently utilized to explain the distribution of concert. The music streaming service provides an integrated set of tools that allow external access to data and functionality through APIs. With the increasing availability of a large number of online data sources, the study of music can be constructed with such data. This study attempted to analyse and discover the spatial dynamics of rock music live performance at the county-level between 2007 and 2017. Using data extracted from the music streaming platform Spotify, this study aims to examine concert patterns associated with the population demographics and LH industry and to explain spatial heterogeneity in the data. This paper is organized as follows. In Section 2, the data source is introduced and ordinary least squares (OLS) and geographically weighted regression (GWR) methods are summarized. In Section 3, a comparative analysis is conducted on the results of different models regressing concert data against business pattern data. Discussions are presented in Section 4. Section 5 is a concise conclusion.

2. Data and methods

2.1 Data

Spotify is an online music streaming platform launched in 2008, which is also a digital music database (Thomes 2013). To assist with the data collection process, a search tool was developed based on the Spotify API, through which concert information was fetched from the database on Spotify to query the live music events between 2007 and 2017. The concert data was retrieved in tabular format, which allows for a more detailed analysis of the various attributes associated with each concert, such as the time it was held, the artist, and the GPS coordinates of the concert. Locations of the individual concerts were mapped according to each site’s latitude/longitude coordinates. They were then spatially aggregated to county boundaries as the county-level dataset has
been proved capable of providing a large enough sample size for the exploration of spatial patterns across the study area (Light and Harris 2012). The analysis of concerts within the contiguous United States was restricted to 3,108 counties across the lower 48 states and Washington DC. (Figure 1).

The demographic factors were chosen as the explanatory variables by their potentials to influence concert distributions. They are characterized by variables regarding population, educational attainment, language spoken, employment status and gender. The data for population density per square kilometre, percent of high school graduate or higher (population 18 years and over), percent of the population speak only English (population 5 years and over), employment/population ratio (population 16 years and over) and gender ratio (males per 100 females) were drawn from the 2016 Census Bureau American Community Survey (ACS) 5-Year Estimates. The industry establishment is widely used as a taxonomy classified based on the North American Industry Classification System (NAICS) to identify economic activities by industry. The US census bureau’s County Business Patterns (CBP) defines an establishment as a fixed place of business where some forms of business activities are conducted with employees (Florida and Jackson 2010). In this study, two industry sectors were selected for LH establishments: Arts, Entertainment, and Recreation (AER, NAICS code is 71) and Accommodation and Food Services (AFS, NAICS code is 72). The AER covers companies that offer commercial recreational services including producing, promoting, and participating in live music performances or events. The AFS is defined by a common business purpose focused on a wide range of services offered, such as lodgings, coffee shops, fast-food restaurants and bakeries. The primary data source for county-level LH establishments came from the 2016 CBP dataset, which provides annual information about industry context in individual counties. All datasets mentioned above were downloaded and then were spatially aggregated to derive county-based explanatory variables. The variance inflation factor (VIF) was then conducted to evaluate the multicollinearity of all the explanatory variables. Correlated variables with a VFI higher than 7.5 indicate collinearity will be removed to avoid inflating the model regression.

2.2 Exploratory spatial data analysis methods

In OLS models, regression coefficients are usually estimated by using least-square techniques.

Figure 1. County-level concert, between 2007 and 2017 of the contiguous United States.
\[ y = \alpha + \sum_{j=1}^{n} x_{ij} \beta_j + \varepsilon \]  

(1)

In equation (1), \( \alpha \) is the intercept, \( \beta_j \) is the regression coefficient, \( \varepsilon \) is the residual term, given by the difference between observed and expected value. It is assumed that the \( \varepsilon \) term is normally distributed with constant variance and is independently distributed among observations. Under these assumptions, the regression coefficient can be obtained by (Brunsdon, Fotheringham, and Charlton 1996):

\[ \hat{\beta} = (X^T X)^{-1} X^T y \]  

(2)

In GWR models, regression coefficients are localized and determined for each location individually. For each location \( i \), a separate regression model is carried out as below:

\[ y_i = \alpha(u_i, v_i) + \sum_{j=1}^{n} x_{ij}(u_i, v_i) + \varepsilon_i \]  

(3)

In equation (3), \( y_i \) is the response variable at location \( i \), \( \alpha \) is the intercept, \( u_i \) and \( v_i \) are spatial coordinates of location \( i \), \( x_{ij} \) is the \( j \)th explanatory variable at location \( i \), \( \beta_j \) is the regression coefficient for the \( j \)th explanatory variable, \( n \) is the number of explanatory variables, and \( \varepsilon_i \) is the residual error term at location \( i \) (Brunsdon, Fotheringham, and Charlton 1996).

The estimate of the regression coefficient is given as:

\[ \hat{\beta}_j(u_i, v_i) = (X^T W_i(u_i, v_i) X)^{-1} X^T W_i(u_i, v_i) y_i \]  

(4)

\[ W_i = \begin{bmatrix} w_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{im} \end{bmatrix} \]  

(5)

In equation (4), \( \hat{\beta}_j \) is the estimate of the regression coefficient \( \beta_j \), \( X \) is the design matrix of explanatory variables, \( W_i \) is the diagonal weights matrix as shown in equation (5), \( w_{i1}, \ldots, w_{im} \) are calculated by a weighting function for location \( i \), and \( m \) is the number of surrounding locations of location \( i \) (Brunsdon, Fotheringham, and Charlton 1998).

A weighting function weights the attributes of nearby locations more highly than it does the attributes of distant locations (Brunsdon, Fotheringham, and Charlton 1998). The weighting function is defined as:

\[ W_{ij} = e^{-d_{ij}^2/b^2} \]  

(6)

In equation (6), \( W_{ij} \) is the geographic weight of location \( j \) for location \( i \), \( d_{ij} \) is the distance between location \( i \) and location \( j \) (the surrounding location of \( i \)), and \( b \) is bandwidth (Fotheringham, Brunsdon, and Charlton 2002). In this study, the GWR was carried out using a Gaussian kernel with an adaptive bandwidth which is derived by minimizing the corrected Akaike Information Criterion (AICc) value (Gollini et al. 2013; Kim and Nicholls 2016).

Regression modelling was carried out using OLS and GWR methods. Both were obtained using the ArcGIS Modelling Spatial Relationships toolset. Based on the US census bureau’s 2017 metropolitan and micropolitan statistical area definition, regression modelling was conducted with three distinct groups of samples of all counties, metropolitan counties and non-metropolitan counties separately (Table 1).

### 2.3 Measures of goodness of fit

The R² measures how well a linear model fits a set of observations. The value of R² represents the proportion of variance that is explained by a linear model. In general, the higher the R² value, the better the model fits data. The R² value is calculated by dividing the sum of squares of residuals (SS_RES) by the total sum of squares (SS_TOT) and then subtract it from 1:

\[ R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \]  

(7)

The adjusted R² was used to compare models with different numbers of explanatory variables. The adjusted R² value can be calculated as:

\[ AdjustedR^2 = 1 - \frac{SS_{RES}}{SS_{TOT} - \frac{N - P - 1}{N}} = 1 - \frac{(1 - R^2)(N - 1)}{N - P - 1} \]  

(8)

In equation (8), \( N \) is the sample size and \( P \) is the number of explanatory variables.

A model selection approach was used based on the R², adjusted R² and AICc to select the best set of predictor variables. The R² obtained from GWR shows how this model can fit the data in regression points. The closer a R² is to 1, it leads to better goodness of fit in regression points (Fotheringham, Brunsdon, and Charlton 2002).

\[ AICc = -2L + 2P + \frac{2P(P + 1)}{N - P - 1} \]  

(9)

The measure of goodness of fit used to evaluate the fit of the model is the AICc. Differing from R², AICc has no ‘absolute scale’ but can be used to perform model comparisons (Snipes and Taylor 2014). In equation (9), \( L \) is a log-likelihood function, \( N \) is the sample size and \( P \) is the number of explanatory variables (Brewer, Butler, and Cooksley 2016). A smaller value of AICc suggests that the model explains the observed data better.
Table 1. Models fitted by regressing rock concert numbers against demographic variables and LH establishments.

| Model # | Model Name | Model | Regression Method |
|---------|------------|-------|-------------------|
| All-county model | All-county EDU | \( T_{all} = a + \beta_{1}EDU_{all} \) | OLS |
| 1 | All-county LANG | \( T_{all} = a + \beta_{1}LANG_{all} \) | OLS |
| 2 | All-county EMP | \( T_{all} = a + \beta_{1}EMP_{all} \) | OLS |
| 3 | All-county GNDR | \( T_{all} = a + \beta_{1}GNDR_{all} \) | OLS |
| 4 | All-county AER | \( T_{all} = a + \beta_{1}AER_{all} \) | OLS/GWR |
| 5 | All-county AFS | \( T_{all} = a + \beta_{1}AFS_{all} \) | OLS/GWR |
| 6 | All-county POP | \( T_{all} = a + \beta_{1}POP_{all} \) | OLS/GWR |
| 7 | All-county LH-POP | \( T_{all} = a + \beta_{1}AER_{all} + \beta_{2}AFS_{all} + \beta_{3}POP_{all} \) | OLS/GWR |
| Metro-county model | Metro-county EDU | \( T_{metro} = a + \beta_{1}EDU_{metro} \) | OLS |
| 9 | Metro-county LANG | \( T_{metro} = a + \beta_{1}LANG_{metro} \) | OLS |
| 10 | Metro-county EMP | \( T_{metro} = a + \beta_{1}EMP_{metro} \) | OLS |
| 11 | Metro-county GNDR | \( T_{metro} = a + \beta_{1}GNDR_{metro} \) | OLS |
| 12 | Metro-county AER | \( T_{metro} = a + \beta_{1}AER_{metro} \) | OLS/GWR |
| 13 | Metro-county AFS | \( T_{metro} = a + \beta_{1}AFS_{metro} \) | OLS/GWR |
| 14 | Metro-county POP | \( T_{metro} = a + \beta_{1}POP_{metro} \) | OLS/GWR |
| 15 | Metro-county LH-POP | \( T_{metro} = a + \beta_{1}AER_{metro} + \beta_{2}AFS_{metro} + \beta_{3}POP_{metro} \) | OLS/GWR |
| Nonmetro-county model | Nonmetro-county EDU | \( T_{nonmetro} = a + \beta_{1}EDU_{nonmetro} \) | OLS |
| 17 | Nonmetro-county LANG | \( T_{nonmetro} = a + \beta_{1}LANG_{nonmetro} \) | OLS |
| 18 | Nonmetro-county EMP | \( T_{nonmetro} = a + \beta_{1}EMP_{nonmetro} \) | OLS |
| 19 | Nonmetro-county GNDR | \( T_{nonmetro} = a + \beta_{1}GNDR_{nonmetro} \) | OLS |
| 20 | Nonmetro-county AER | \( T_{nonmetro} = a + \beta_{1}AER_{nonmetro} \) | OLS/GWR |
| 21 | Nonmetro-county AFS | \( T_{nonmetro} = a + \beta_{1}AFS_{nonmetro} \) | OLS/GWR |
| 22 | Nonmetro-county POP | \( T_{nonmetro} = a + \beta_{1}POP_{nonmetro} \) | OLS/GWR |
| 23 | Nonmetro-county LH-POP | \( T_{nonmetro} = a + \beta_{1}AER_{nonmetro} + \beta_{2}AFS_{nonmetro} + \beta_{3}POP_{nonmetro} \) | OLS/GWR |

\( T_{all} \) and \( T_{nonmetro} \) is the total number of rock concerts in both metropolitan and non-metropolitan counties, respectively. \( EDU_{all} \) and \( EDU_{nonmetro} \) is the percent of population graduated high school or higher degrees (18 years and over) in both metropolitan and non-metropolitan counties, respectively. \( LANG_{all} \) and \( LANG_{nonmetro} \) is the percent of population speak only English (5 years and over) in both metropolitan and non-metropolitan counties, respectively. \( EMP_{all} \) and \( EMP_{nonmetro} \) is the employment/population ratio (16 years and over) in both metropolitan and non-metropolitan counties, respectively. \( AER_{all} \) and \( AER_{nonmetro} \) is the number of AER establishments in both metropolitan and non-metropolitan counties, respectively. \( AFS_{all} \) and \( AFS_{nonmetro} \) is the number of AFS establishments in both metropolitan and non-metropolitan counties, respectively. \( POP_{all} \) and \( POP_{nonmetro} \) is the population density per square kilometre in both metropolitan and non-metropolitan counties, respectively.

3. Results

In order to investigate whether the live music industry is related to selected factors, OLS regression analysis was conducted regressing rock concert numbers against seven variables including percent of population (18 years and over) graduated high school or higher degrees (EDU), percent of population (5 years and over) speak only English (LANG), population (16 years and over) (EMP), gender ratio (males per 100 females) (GNDR), AER establishments (AER), AFS establishments (AFS) and population density per square kilometre (POP). The coefficients had the expected signs that EDU, EMP, AER, AFS and POP displayed positive parameter coefficients, while LANG and GNDR displayed negative parameter coefficients (Table 2). The variance inflation factor (VIF) – a measure of redundancy among explanatory variables AER (3.0 and 3.0), AFS (3.4 and 3.3) and POP (1.3 and 1.2) was less than 7.5 for all-county LH-POP model and metro-county LH-POP model separately, suggesting the lack of multicollinearity problems among the explanatory variables (Gollini et al. 2013; Comber et al. 2020). The p-value showed the high statistical significance of most models.

For the all-county model, the global model fit (OLS) gave both R² and adjusted R² values higher than 0.5 when regressing the number of concerts against AER and POP, which indicates that over half of the variation in the number of concerts could be explained using LH establishments. While other variables exhibit a statistically significant relationship with the number of concerts but can barely explain model variances except for POP (R² = 0.22 and adjusted R² = 0.22),
which implies that EDU, LANG, EMP and GNDR not appearing as powerful explanatory variables in regression models of concerts. Among all metro-county models, LH-POP is the best fitted OLS model with more than 80% of the variation explained by the model. Both R² and adjusted R² values for OLS models with AFS are higher than OLS models with AER, indicating a better performance of models with AFS. The value of AICc also shows OLS models with AFS (32,845.92) outperformed OLS models with AER (35,082.80). The metro-county AFS model is with higher R² (0.79) and higher adjusted R² (0.79) values than values for the metro-county AER model (R² = 0.56, adjusted R² = 0.56) and values for the metro-county POP model (R² = 0.21, adjusted R² = 0.20).

It also can be seen that the metro-county AFS model outperforms the metro-county AER model and the metro-county POP model with lower AICc values indicating better model fit. EDU, LANG, EMP and GNDR were excluded from GWR models due to their lack of explanatory power regarding OLS regression results. Similarly, the nonmetro-county model was not as effective at explaining the variation in concerts with relatively poor R² values. Due to its weak fit, the non-metro-county model was not included in the GWR analysis.

The GWR model was carried out in consideration of possible regional heterogeneities in factors that potentially affect the spatial distribution of concert across US counties. The R² and adjusted R² obtained using GWR (0.87 and 0.87 for all-county LH-POP model, 0.89 and 0.85 for all-county AER model, 0.87 and 0.85 for all-county AFS model, 0.66 and 0.60 for all-county POP model respectively) implied a considerable improvement of model performance with respect to R² and adjusted R² of using OLS (0.80 and 0.80 for all-county LH-POP model, 0.57 and 0.57 for all-county AER model, 0.79 and 0.79 for all-county AFS model, 0.22 and 0.22 for all-county POP model respectively). Likewise, the AICc of GWR models related to model error was smaller than those of OLS models, suggesting a better fit of data by the GWR model than by the OLS model. Additionally, as can be seen in Table 2, the GWR LH-POP model has higher adjusted R² values and lower AICc than AER model, AFS model and POP model. Such results indicate improved model performance by considering both LH establishments and population density compared with GWR models with a single explanatory variable. The GWR metro-county AFS model was also found with higher adjusted R² and lower AICc than the GWR metro-county AER and GWR metro-county POP models, implying a better explanatory capability of AFS than AER and POP in metropolitan areas.

The local R² values of all-county models (i.e. AER model, AFS model, POP model and LH-POP model) were mapped in Figure 2 to present the spatial variation of the model’s explanatory power. As shown in Figure 2, the spatially varying local R² values indicate spatial heterogeneity in local parameter estimates that are not the same across space. As can be seen in these figures, the amount of R² is changed spatially for different areas. The closer local R² is to 1 the better goodness of fit is of a model (Fotheringham, Brunsdon, and Charlton 2002). According to Figure 2, the all-county LH-POP model was best fitted with LH establishment and demographic data of counties located in the West, Southwest, the Great Lakes and Mid-South regions. On the other hand, relatively lower local R² values less than 0.8 are in the part of Southeast, Midwest, Northeast, upper Great Plains and

Table 2. Results of county-level regression analyses.

| Model | Coefficient | p-value | Adjusted R² | AICc | Method |
|-------|-------------|---------|-------------|------|--------|
| 1     | 0.94        | 0.001696* | 0.00        | 0.00 | 37,711.97 | OLS |
| 2     | -2.04       | 0.000000* | 0.05        | 0.05 | 37,558.48 | OLS |
| 3     | 1.63        | 0.000000* | 0.02        | 0.02 | 37,669.07 | OLS |
| 4     | -0.61       | 0.000143* | 0.00        | 0.00 | 37,707.24 | OLS |
| 5     | 0.26        | 0.000000* | 0.57        | 0.57 | 35,082.80 | OLS |
| 6     | -0.12       | 0.000000* | 0.89        | 0.85 | 32,528.09 | GWR |
| 7     | 0.10        | 0.000000* | 0.79        | 0.79 | 32,845.92 | OLS |
| 8     | -0.04       | 0.000000* | 0.80        | 0.80 | 32,680.07 | OLS |

* Coefficient and p-value for explanatory variable: AER establishments.
** Coefficient and p-value for explanatory variable: AFS establishments.
*** Coefficient and p-value for explanatory variable: population density per square kilometre.

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Similar to the all-county AER model, all-county AFS model and all-county POP model show spatially varying relationships regressing concert against LH establishments and population density within the study area. The all-county AER model was better fitted in the metropolitan and micropolitan areas with a local $R^2$ value larger than 0.9 and lower local $R^2$ values less than 0.75 are mostly located in the Rocky Mountain regions.
non-metropolitan areas. By using AFS establishment data, the GWR model can explain more than 75% of the spatial variation of concerts in more than half of metropolitan counties. Higher values of $R^2 (>0.9)$ for all-county AFS models are apparent in southern California, northern Illinois and southern Texas where large cities such as Los Angeles, Chicago and Houston are located. In general, the all-county LH-POP model exhibits superior explanatory power modelling concerts over the all-county AER model, all-county AFS model and all-county POP model, which is in line with the OLS results. Therefore, the all-county LH-POP model was undergoing further investigations on its local multicollinearity, residuals autocorrelation and non-stationarity of regression coefficients.

Local multicollinearity issues found in a GWR model can invalidate interpretations of regression coefficient estimates and lead to misleading conclusions (Wheeler and Tiefelsdorf 2005). Therefore, the GWR multicollinearity investigation was performed through the visualization of condition numbers. Most research has suggested that multicollinearity is unproblematic where the condition number is less than 30 (Gollini et al. 2013; Comber et al. 2020). Figure 3a shows that the condition numbers were classified using Jenks natural breaks and the effects of multicollinearity are substantially stronger in part of Midwest and South regions. In general, condition numbers across the study area are less than 30, which implies that the local multicollinearity is negligible.

The LISA analysis measures the degree of spatial autocorrelation locally at each county using a localized Moran’s I (Javi, Malekmohammadi, and Mokhtari 2014). Results of LISA analysis of the residuals for the all-county LH-POP model demonstrate very little local spatial autocorrelation. Spatially, the result implies that all-county LH-POP model accounts for spatial non-stationarity of variables efficiently. This is displayed through very minimal statistically significant clustering (i.e. residuals are not clustered with other comparative residuals). According to Figure 3b, High-High (HH) autocorrelation was observed only in the western and northeastern parts. Also, High-Low (HL) and Low-High (LH) autocorrelations were mainly found in California, Washington, New York and New Jersey. Generally, in most counties, no significant (NS) spatial autocorrelation was observed.

**Figure 4.** (a) LH-POP model regression coefficient of AER; (b) LH-POP model regression coefficient of AFS; (c) LH-POP model regression coefficient of POP.
The estimated regression coefficients were mapped by a multi-hued colour scheme (Figure 4). The patterns of regression coefficients show that the positive relationships do not hold across space. Different signs of coefficients between AER and AFS mainly appear in Rocky Mountain, Midwest, Southwest and part of Southeast counties. Coefficients of POP are positive in a large area across space except in some counties located in Southwest, Midwest and Southeast regions. In general, GWR results are consistent with OLS results regarding the goodness of fit and parameter estimates of models.

4. Discussion

Research on audience demographics has found that music audiences are generally middle class and in the higher educated proportion of the general population (Toma and Meads 2007; Willekens and Daenekindt 2020). This is in line with the finding that concerts are in positive correlations with education attainment and employment status. Indicators of the local population demographic profile such as education attainment, language, employment status and gender show statistically significant relationships with concerts but with relatively lower R² values, which implies that demographic characteristics of local population can only explain variations of concerts partially. This is mainly due to the impacts of tourists (e.g. fan travellers and regular visitors) over the local population on the live music industry. Music can be an important tourism product of the leisure and hospitality industry and the growing significance of live music such as music festivals and concerts as a tourist attraction is evidenced worldwide (Arcodia and Whitford 2007). The tourism flow contributes a large share of total concert revenues (Gnuschke and Wallace 2004). Being in close proximity to the tourism market is of importance to musicians (Basu and Imara, 2014). As a result, in some cultural economy leading regions, music tourism can lead to rapid cultural and economic changes including local demographic shifts (Gibson and Connell 2003).

The changes in concert distribution in relation to the LH industry’s economic patterns are evident in the whole study area, which agrees with (Krueger 2005) that fundamental economic forces are playing important roles in the music industry. In this study, the number of LH establishments exhibits positive coefficients of all OLS models, which allow us to infer that the LH industry is vital for the live music industry. Generally, the AFS sector comprises two distinct services to meet very basic human needs, the provision of accommodation and the provision of sustenance for eating (Anita and Liana 2010). Whenever people come together for music events, there is a need for hospitality services. Therefore, hospitality businesses, such as restaurants, hotels/motels and bars are important to gatherings of live music artists and spectators. At the same time, promoting the music business was also believed to be helpful to the growth of the tourist and hospitality industry especially in the hotel and retail development (O’meara and Tretter 2013). The result shows that over 85% of concert variations can be explained by AFS establishments, implying that accommodation and food services determine factors in choosing a performance site for artists and choosing a trip destination for music tourists. Apart from hospitality services, this study also shows that the entertainment industry can also be used to explain concert distribution. The result shows that nearly 90% of concert variations were explained by AER establishments emphasizing the importance of an area’s AER infrastructure as an explanation for why concert clusters geographically. This finding agrees with (Mangaoang and O’Flynn 2016) that the accessibility to AER facilities such as venues is an essential factor for a ‘city of music’. Some cities seek to market themselves with musical activities to attract tourists and promote their music venues and live music scenes (Kong 1995; Halfacree and Kitchin 2000; Gibson 2007). For instance, the city of Liverpool has seen the economic benefits of music-based developments (Hudson 2006). Actually, the economies of tourist destinations such as New York City, Los Angeles, Las Vegas and Reno have been reshaped by the performance and consumption of music (Florida, Mellander, and Stolarick 2010). (Lashua, Spracklen, and Long 2014) also confirmed that music has the ability to transform places into tourist hotspots. Because of the capability of servicing music tourists at concerts and festivals, a large number of establishments operating entertainment venues and other recreational facilities can attract artists to agglomerate in AER service industry-leading areas.

The metro-county model exhibits superior explanatory capability than the non-metro-county model regarding OLS results, reflecting the economic advantages of AFS and AER industries in metropolitan areas. The capability of the venue is an important factor that artists consider for their concerts (Papies and van Heerde 2017). Metropolitan areas have easy access to entertainment venues and sizable facilities such as arenas and stadiums with large seat capabilities for live music performances (Holt and Lo 2008; Deichmann 2014; Verboord and Noord 2016). Additionally, metropolitan areas have larger markets and more demand for music performance (Florida, Mellander, and Stolarick 2010). Moreover, dense agglomerations of employment in the
cultural economy are usually concentrated in metropolitan areas (Scott 1997). (Ellis and Beresford 1994) believed that there is a large size of the labour force in a metropolitan area. The local labour force with an abundance of skills, inputs, and capabilities supports the music industry (Florida et al. 2012). In contrast, high rents and the absence of venues make live music uncommon in suburban areas and where involvement in rock culture is also shaped differently from urban areas (Straw 1984). As a result, musicians are attracted primarily by large urban areas and choose to perform close to these regions with their desired population size and market size (Deichmann 2014). This was demonstrated by results that population density has a positive correlation with concert distributions and exhibits superior explanatory power than other major demographic factors in models. Metropolitan size is also important to concert site selections (Johansson and Bell 2014). This study confirmed this by finding that a region is generally attractive to more concerts when being or being closer to large metropolitan areas such New York metropolitan area, Los Angeles metropolitan area and Chicago metropolitan area (Figure 1). The North American metropolitan areas are still undergoing growth and urban sprawl (Torrens 2008; Debbage, Bereitschaft, and Shepherd 2017). Therefore, future work is needed to explore urbanization impacts on rock performance dynamics in multiple temporal snapshots.

The spatial dynamics of variables related to concerts were believed to result in an uneven distribution of performance (Deichmann 2014). The location of the music industry is highly concentrated and is driven by economies (Florida, Mellander, and Stolarick 2010). Some places gained economic success due to music festivals whereas others are undergoing economic setbacks because of less attractive to musical business (Verboord and Noord 2016). By modelling economic data against concert data, concerts occur in observable structures associated with LH establishments. The map of local R^2 (Figure 2) indicated variations in local parameter estimates over space. This is consistent with a finding that the decisions musicians make about where to perform concerts reflect economic differences among cities (Johansson and Bell 2014). The model appears with higher R^2 values where big cities are located. A finding could explain that concerts tend to be located close to a specific location such as the periphery of a megaregion and areas that may likely be an economy ‘hub’ (Johansson and Bell 2014). New York, Los Angeles and Chicago were found to be the dominant locations, which could be explained by the fact that large cities offer access to large markets and play an important role in commercializing and popularizing music (Florida and Jackson 2010). Musicians aim to grow their fan base in concerts (Gibson 2007). Therefore, a live performance is usually designed to maximize profit to attract as many concert attendees as possible by emphasizing larger markets (Johansson and Bell 2014). Meanwhile, the service industry and consumption city centre attract tourists and visitors through music promotions (Halfacree and Kitchin 2000). As a result, a place with more LH establishments to serve tourists and a higher population density has implications upon this place’s market with a larger number of spectators that musicians can reach.

There is a long tradition in music studies linking relational and physical spaces. For instance, the study of music festivals can reveal the changing nature of the site where it is hosted (Gibson 2007). In the process of the theorization of the geographies of the performing arts, performance has finally extended existing approaches for examining a variety of geographical phenomena (Rogers 2018). This paper complements findings on spatialities of concert location selection that was made by many articles showing the geographic importance of metropolitan areas but providing evidence from a different data source. New opportunities emerge as the music streaming platform could provide data sources through API services. In this study, integrating ‘geography’ with music is mainly based on the location information of the concert. The location of the concert is an important geographic feature reflecting the spatial dynamics of music. Geo-tagged information of concert data is essential to analysing live music industry as it can provide clues for identifying the most favourite destination of live music performance, assisting in the design of music festivals, aiding in the promotion of concert tour, and helping gain a better understanding of environmental factors that may affect the musician’s behaviours. For this study, a novel approach was taken to carry out this task. Each of these rock concerts was retrieved by Spotify API, which greatly improves the ability to identify concert counts for individual counties accurately.

The rock music industry started as a social movement and gave rise to economic changes (Connolly and Krueger 2006). However, the conventional economic variables have limited power to model musician behaviours (Florida, Mellander, and Stolarick 2010). Most social behaviours or phenomena are embedded in a geographic context characterized by spatial heterogeneity. For instance, unlike other consumptive services, concert exhibits geographic unevenness (Johansson and Bell 2014). Moreover, the number of concert audiences could vary greatly depending on the geographic location (Tilly 2013).
This paper is particularly interested in identifying concert patterns and determining whether these patterns are randomly distributed due to chance, or if there is a tendency for a set of cases to statistically group or cluster. A majority of empirical music studies that have used descriptive analysis fail to discern spatial variations in statistical relationships. This paper addresses previous limitations of regression analysis through the use of GWR to examine economic associations with concert distributions. The application of GWR is highly useful for understanding parameter heterogeneity in data thereby enabling assessment of the spatial effects of the model. Therefore, this study provides new perspectives on examining rock music dynamics using concert data extracted from web resources and informs the selection of economic features that are closely linked to live performance destination selection.

5. Conclusions

This study attempted to map concerts to target the markets where rock music can sell the best by identifying a valuable alternative to the lengthy and costly collection of concert data via an online music streaming platform and its API services. Advanced geospatial methods were then applied to examining county-level rock concert data, population demographic data and LH establishment data in order to gain insight into the venue selection. OLS models were best fitted in metropolitan areas where service industry-leading cities such as New York City, Los Angeles, Chicago and Houston are located. The spatial heterogeneity in the county-level concert data was properly considered in the development of GWR models. GWR models overall explained 87% of the county-level variation in rock concerts and local $R^2$ values were between a range of 0.59 and 0.96 for counties within metropolitan areas. The local $R^2$ values also revealed that the relationships between concerts and LH establishments are more important than the relationships between concerts and population demographics and display significant spatial non-stationarity. Both OLS and GWR models provide insights underscoring the importance of metropolitan areas to live music performances over non-metropolitan areas.

This study has emphasized the value of using LH industry information in explaining the patterns of concerts by analysing spatially nonstationary relationships between concerts and establishments. The results imply that for the live music industry, the LH industry has special importance as accommodation, food and leisure services that constitute a major contribution to meeting the needs of live music performance. Additionally, results also have implications on the importance of understanding live music market demand and uncovering this information can be accomplished through analysing demographic characteristics such as population density. Although the analysis is limited to the sample of actively touring artists during 2007–2017, it has implications for future musicians’ destination choices. This study has identified 250 counties that are the major destination of over 90% of concerts between 2007 and 2017. Such cartography of concert can be used by authorities when planning large music festivals, or targeted advertising of music events in practice. Musicians and music companies can also seek to locate their site according to this study using results about the most ‘rock’ areas to project the viability of their intended business.

Disclosure statement

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