Long-range dependence and Trends in Nigerian Popular Music Artists' Famosity-"Davido", "Burna Boy", "Tiwa Savage" and "Wizkid": Evidence from Google Trends

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30 November 2020

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Abstract

We investigate long-range dependence and linear trend in the famosity of popular Nigerian music artists such as Davido, Burna Boy, Tiwa Savage, and Wizkid by relying on their Web, News, Image and YouTube Google Trends searches. The available weekly datasets span 13.09.2015 to 06.09.2020. Preliminary results indicate correlations of search parameters (Web, News, Image and YouTube) of each musicians, while correlations of each search popularity parameters are weaker across musicians. Upon applying fractional persistence approach, we obtain that Web searches for these four musicians have slower tendencies to revert to mean level compared with persistence estimates for News, Image and YouTube searches, while Burna Boy weekly popularity indicate positive linear trend across the four search parameters. This musician is likely to pull more online support in few years than other music youngsters.

Keywords: Long-range dependence; Pop music; Google Trends

1. Introduction

Popular music is a brand of music that has massive consumers across the world. For Shah (2006), popular music can be regarded as the most preferred music style, having a wide appeal with the help of mass media. It is a music genre that is associated with urban spaces and dominated by youths. Popular music is made popular through mass media, radio, television, and recently the internet (Shah 2006; Law and Ho 2015; Ojukwu, Obieloze and Esimone, 2016). Young people's engagement with popular music has been observed in the literature. Law and Ho (2015, 305) observed that "popular music has long been integral to many young people's daily lives, and the post-Second World War media has intensified this trend". Similarly, Walker (2001, 16) observed that young people enjoy listening to popular music and are "willing to invest time and money as listeners". The way and manner people especially the youths engage with music has changed drastically and technology is reported to be a major determinant. Media technologies such as radio, television, the internet, and personal portable devices, such as MP3 players and smartphones provide easy and seamless access to popular music to youths in many countries.

Popular musicians are gaining a level of recognition at various degrees in different countries. This recognition elevates some of these musicians to the status of celebrities. The notion of celebrity is associated with various sectors including entertainment, sports, business, and politics (Hellmueller and Aeschbacher 2010). For instance, a celebrity musician may also be a successful actor or actress. This dual- or tri-celebrity positionality makes them trendy both in the music and outside the music scene. Because of their 'publicness' as celebrities, they have large fandom that is not only interested in their artistic offerings but also in their everyday lives such as love life, finance, and fashion. In order words, popular musicians are not only trendy online essentially for their music.

The age of digital and internet technologies has made contact between celebrities and their fans very seamless. In fact, there are almost no barriers between the two parties. Musicians are now regularly feasible on various internet platforms where their fans can get to know about their lifestyle. In addition, their musical works are uploaded and available for live streaming or downloading sometimes for a fee. The internet, beyond serving as a viable publicity space for musicians, it also helps in the economic activities of the musicians. It is now common practice for musicians to premiere their musical works online instead of the normal concert hall performance.

This trend in the use of the internet to advance the music economy is of growing interest to both scholars and practitioners. Real-time information as per what music and which musicians people search for online is helpful for stakeholders in the music business. At the click of a button, digital music promoters can access several pieces of information about the music they are promoting. For example, modern technology can show the number of people who searched for a particular musician per day, the locations of the people, and the times when they checked this music can be displayed. This is made possible through various search engines such as Google.

Among all the different search engines that are available on the internet, google is considered the most widely used. Because of its versatile utility, google has other several functions that make search expeditions easy and detailed. Such of which is google trend.

Google Trends gives access to large unfiltered searches on Google. The searches are anonymized, categorized, and aggregated, forming time-series observations. Thus, the interests of people within geographical locations, around the globe are displayed. Terms or keywords are searched and these are divided by the total searches within a particular geographical location and within a time range. So, the relative popularity of such terms/keywords is obtained and this is scaled on a range 0 to 100 based on its proportion to all searches on all topics. Though Google Trends reflects daily or real-time searches people make on Google but these searches may also include spammer's attempt, while Google has a way of filtering off this irregular activity.[1]

The present paper investigates long-range dependence and trend in the famosity of Nigerian music artists by using their interest data on Google. We consider four music artists and they include Davido, Burna Boy, Tiwa Savage, and Wizkid. The updated nonlinear fractional persistence approach was used for the analysis of the time series. Persistence is a

[1] Note, Google Trends are reported for popular terms and search terms with very low volume are scored 0.

function of noise level in a particular time series, while a less noise series is expected to have higher persistence level compared to a more noised time series. The persistence approach allows one to investigate long-range dependency in which long memory is a subset. The long memory property in the sense that observations over a long lag span are still found to be dependent on the current observation. Thus, the future can easily be mimicked by current trends of observations. These dependencies are given by sample autocorrelations that decay slowly over long legs. This is also a function of amount of noise in the time series, where a less noised series is expected to be highly persistent. Using the present data to explain, with a long memory, it implies that the interests/popularity of a particular musician depends solely on immediate and long-time past interests on Google Trend.

2. Data and Preliminary results

Search volumes relating to each of four Nigerian popular music artists - Davido, Burna Boy, Tiwa Savage, and Wizkid, were obtained from the Google Trends database (https://trends.google.com/trends/?geo=NG), considering only searches specific to Nigeria. These search volumes are used to proxy peoples' interests in the mentioned music artists, thus giving a measure of their famosity within the country. Four search sources were considered and they include Image, Web, News, and YouTube searches. The weekly frequency search volumes relating to each music artist and specified search sources, and spanning 13.09.2015 to 6.09.2020, were analyzed in this study, given the available data volume for the past 5 years.

Table 1 presents the summary statistics (mean, standard deviation, coefficient of variation, skewness, and kurtosis) of the search volumes relating to each of the four music artists by search sources (Web, News, Image, and YouTube). Among the music artists considered, Wizkid appears to be the most searched music artist on Web, News, and Image searches, while Burna Boy is the most searched on YouTube. Burna Boy is the least searched music artist on Web, News, and Image, while Tiwa Savage is the least searched on YouTube. Davido is consistently the second most searched music artist on all four search sources. Search volumes relating to Wizkid (Web, News, and Image) and Davido (YouTube) over the period being considered varied the least, judging by the coefficient of variation, and the highest variation was found for the case of Burna Boy (Web, News, and Image) and Tiwa Savage (YouTube). All search volumes relating to the four music artists from the four different search sources are found to be positively skewed and leptokurtic, exhibiting excess kurtosis. This translates to the non-normality of the search volumes, regardless of the music artist considered. We present the plot of people's interests in these musicians in Figure 1, based on Web, News, Image, and YouTube searches.

Table 1: Descriptive Statistics of measure of Music Artists' Famosity

	Web search				**News search**			
Searches	**Burna Boy**	**Davido**	**Wizkid**	**Tiwa Savage**	**Burna Boy**	**Davido**	**Wizkid**	**Tiwa Savage**
Mean	19.27	28.24	30.87	19.46	16.07	31.00	41.80	22.16
Median	11.00	27.00	27.00	17.00	13.00	28.00	39.00	20.00
Maximum	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Minimum	2.00	9.00	15.00	6.00	0.00	6.00	14.00	0.00
Std. Dev.	17.91	13.76	12.27	11.39	20.07	16.22	14.62	19.72
Skewness	1.30	1.01	1.79	2.74	1.37	1.22	0.98	1.29
Kurtosis	4.51	5.28	7.77	16.13	4.84	4.88	4.72	5.46
	Image search				**YouTube search**			
Searches	**Burna Boy**	**Davido**	**Wizkid**	**Tiwa Savage**	**Burna Boy**	**Davido**	**Wizkid**	**Tiwa Savage**
Mean	20.56	38.41	52.58	30.98	28.34	25.91	12.02	10.49
Median	14.00	36.00	52.00	30.00	23.00	23.00	11.00	9.00
Maximum	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Minimum	0.00	14.00	19.00	9.00	0.00	4.00	4.00	0.00
Std. Dev.	19.69	13.42	13.21	12.10	20.90	13.65	7.48	9.94
Skewness	1.34	1.26	0.43	1.52	1.02	1.70	6.88	4.80
Kurtosis	4.98	5.79	3.67	8.01	3.67	8.27	76.16	36.29

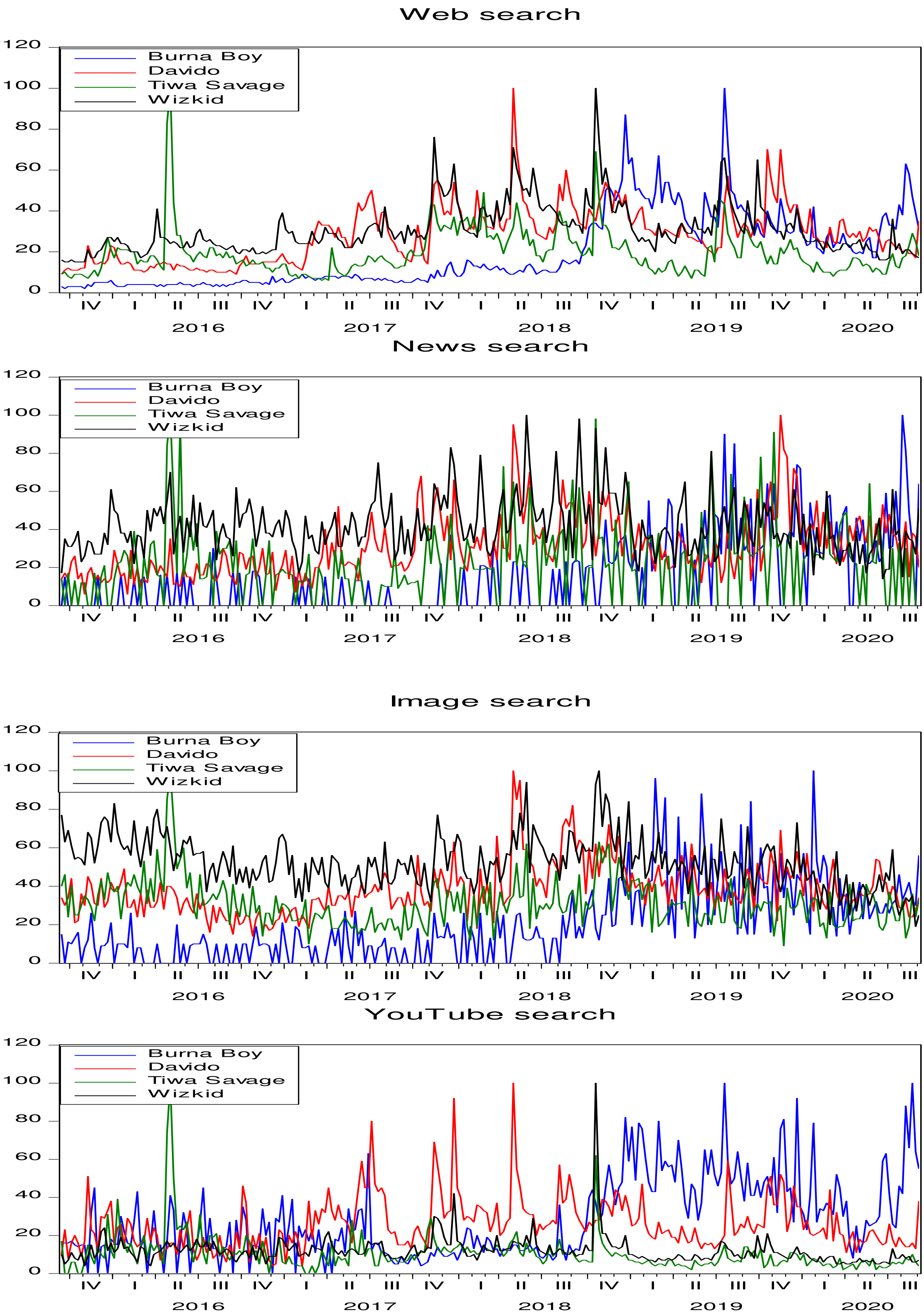

Figure 1: Plots of Google Search Volumes through Web, News, Image, and YouTube

Table 2 presents the Pearson's correlation estimates of music artists' famosity by search sources' pairs (top panel) and by music artists' pairs (bottom panel). The search volumes (people's interest) of each music artist across search sources are found to be significantly correlated with the range of correlation ranging between 0.267 and 0.821. For all the music artist, except in the case of Davido, the correlation between the search volumes from News and Image are found to be the least, while Web and YouTube show the highest level of correlation. On music artists' pairs, we find a significant positive correlation between Davido and Wizkid, Davido and Tiwa Savage (except under the YouTube search), Wizkid and Tiwa Savage; across the four search sources. The search volumes relating to Burna Boy appear not to be significantly correlated with the other considered music artists, except in the case of YouTube search where it is significantly negatively correlated with search volumes on Tiwa Savage. From the foregoing, the interest of people in the different artists appears to be relatively consistent across the search sources, than between music artists.

Table 2: Pearson Correlation estimates of Music Artists Famosity

Panel A					
Music Artist	**Searches**	**Web**	**News**	**Image**	**YouTube**
Davido	Web	1			
	News	0.721**	1		
	Image	0.688**	0.601**	1	
	YouTube	0.779**	0.519**	0.520**	1
Burna Boy	Web	1			
	News	0.629**	1		
	Image	0.683**	0.521**	1	
	YouTube	0.821**	0.523**	0.601**	1
Tiwa Savage	Web	1			
	News	0.385**	1		
	Image	0.510**	0.267**	1	
	YouTube	0.736**	0.358**	0.566**	1
Wizkid	Web	1			
	News	0.523**	1		
	Image	0.447**	0.358**	1	
	YouTube	0.665**	0.418**	0.440**	1
Panel B					
Searches	**Music Artist**	**Davido**	**Burna Boy**	**Tiwa Savage**	**Wizkid**
Web	Davido	1			
	Burna Boy	0.390**	1		
	Tiwa Savage	0.287**	0.051	1	

	Wizkid	0.611**	0.244**	0.545**	1
News	Davido	1			
	Burna Boy	0.191**	1		
	Tiwa Savage	0.135*	0.063	1	
	Wizkid	0.248**	-0.025	0.269**	1
Image	Davido	1			
	Burna Boy	0.261**	1		
	Tiwa Savage	0.183**	-0.086	1	
	Wizkid	0.317**	-0.114	0.423**	1
YouTube	Davido	1			
	Burna Boy	0.007	1		
	Tiwa Savage	0.046	-0.133*	1	
	Wizkid	0.298**	-0.115	0.427**	1

Note, ** and * denotes significant two-tailed correlation estimates at 1 and 5% levels, respectively.

3. Fractional persistence and the results

We describe long-range dependence (LRD) in the popularity searches of these musicians in this section of the paper. LRD is a property of a fractional persistent stochastic process that is time-dependent. In a time series X_t which is supposed to be either a stationary or non-stationary stochastic process, transformed stationary fractionally integrated/persistent series is obtained based on the backward shift operation,

$$(1-B)^d x_t = u_t, \qquad t = 1, 2, ... \tag{1}$$

where B is the backward shift operator, such that, $(Bx_t = x_{t-1})$ and u_t is the noise process, assumed to be of short persistence. It is usually denoted as an integrated of order zero process or $I(0)$. Thus, we have within this category, the white noise process but also processes which are stationary in the Auto-Regressive Moving Average (ARMA)-form. The parameter d is the fractional persistence parameter that takes values in stationary and nonstationary time series ranges $(-0.5 < d < 2)$ (see Granger, 1980; 1981; Granger and Joyeux, 1980; Hosking, 1981, etc).

The LRD is a subset of fractional persistence in time series econometrics and the testing framework is often used to examine the nature of the shocks in time-dependent processes. The

LRD is characterized by the strong degree of association between distant observations of distant time lag apart. This is similar to long memory. For example, long memory occurs when $0 < d < 0.5$,which is a stationary fractional persistence range, in which the time series is actually mean reverting, that is, it has the ability to revert to its mean level after an initial shock. The LRD occurs once the values of d goes beyond 0.5 (i.e. $0.5 < d < 1$). Also, in this case, there is a mean-reverting tendency, though the series is becoming more nonstationary. Both LRD and long memory time series cases have tendencies to revert back to their mean levels once triggered by external shocks only that it takes long memory cases quite more time than the LRD cases to revert to mean levels.

In light of the present paper, evidence of long memory or LRD is investigated in the current time series applied in this paper. In Table 3, we present the estimates of fractional persistence parameter d (emanating from three different model structures – model with no regressors, model with intercept only, and model with intercept and linear trend) for each popular music artist under the four different search sources. Under the Web sources, the model with no regressors is observed to better suit the search volume data of all the music artists except for search volume on Burna Boy, where the model with linear trend fits better. However, in all cases, the estimates of d is found to be greater than 0.5. The search volumes on each of the music artists emanating from the Web are non-stationary but mean-reverting. This implies that shocks to search volumes are not likely to be permanent, it may only require a longer period to fizzle out. A similar feat in terms of model choice is found in the case of the YouTube search option as in the case of the Web search option, except that the estimate of d falls in the stationary long memory interval $(0 < d < 0.5)$. Imperatively, search volumes in the YouTube would revert almost immediately after any shock, requiring no external attention. The search volumes on Tiwa Savage and Burna Boy are consistently best fit by the model with no regressors and model with linear trends, respectively. This feat is observed across the search sources. In the case of Davido and Wizkid, the model with no regressor mostly fits best. The estimates of d under the News and Image search options are also in the stationary and long memory interval $(0 < d < 0.5)$, and consequently, the impact of shocks to the search volumes on these music artists will decay quickly.

By looking at the results of selected deterministic terms in Table 4, we consistently find significant linear trend for searches based on Web, News, Image and YouTube for Burna Boy popularity. Thus, the popularity of this music youngster in positively trending over time. Davido also has positively trending News popularity, while Wizkid has negatively trending popularity.

Table 3: Fractional persistence estimates based on Robinson (1994) approach

	No regressors	**An intercept**	**A linear time trend**
		Web	
Davido	**0.6494 (0.5410, 0.7578)**	0.6433 (0.5351, 0.7515)	0.6334 (0.5217, 0.7452)
Burna Boy	0.7164 (0.6200, 0.8128)	0.7109 (0.6153, 0.7597)	**0.6798 (0.5761, 0.7327)**
Tiwa Savage	**0.6437 (0.5798, 0.7076)**	0.6437 (0.5173, 0.7082)	0.6434 (0.5170, 0.7079)
Wizkid	**0.6008 (0.5001, 0.6522)**	0.5965 (0.4963, 0.6476)	0.5950 (0.4943, 0.6464)
		News	
Davido	0.3907 (0.3027, 0.4356)	0.3907 (0.3033, 0.4353)	**0.3470 (0.2512, 0.3959)**
Burna Boy	0.3272 (0.2498, 0.3667)	0.3272 (0.2498, 0.3667)	**0.1598 (0.0673, 0.2070)**
Tiwa Savage	**0.1677 (0.0750, 0.2150)**	0.1682 (0.0755, 0.2155)	0.1565 (0.0610, 0.2520)
Wizkid	**0.2514 (0.1581, 0.2990)**	0.2513 (0.1582, 0.2988)	0.2505 (0.1574, 0.2980)
		Image	
Davido	**0.3994 (0.3130, 0.4858)**	0.3991 (0.3131, 0.4851)	0.3892 (0.3006, 0.4778)
Burna Boy	0.3201 (0.2531, 0.3871)	0.3208 (0.2536, 0.3880)	**0.1986 (0.1224, 0.2748)**
Tiwa Savage	**0.3476 (0.2594, 0.4358)**	0.3476 (0.2594, 0.4358)	0.3376 (0.2480, 0.4272)
Wizkid	0.3794 (0.2941, 0.4647)	0.3794 (0.2941, 0.4647)	**0.3472 (0.2941, 0.4647)**
		YouTube	
Davido	**0.4129 (0.3106, 0.5152)**	0.4129 (0.3100, 0.5158)	0.4112 (0.3087, 0.5137)
Burna Boy	0.4308 (0.3504, 0.5112)	0.4308 (0.3504, 0.5112)	**0.3799 (0.2933, 0.4665)**
Tiwa Savage	**0.4307 (0.3164, 0.5450)**	0.4326 (0.3174, 0.5478)	0.4233 (0.3022, 0.5444)
Wizkid	**0.3290 (0.2237, 0.4343)**	0.3289 (0.2236, 0.4342)	0.3224 (0.2152, 0.4296)

Note, in bold are persistence estimates d selected based on the significance of the deterministic terms in Robinson (1994) framework. The confidence interval of d is in parentheses.

Table 4: Selected results in Table 3

	d. (C.I.)	An intercept coefficient	Linear time trend coefficient
Searches	**Web**		
Davido	0.6494 (0.5410, 0.7578)	…….	…….
Burna Boy	0.6798 (0.5761, 0.7327)	-19.487 (-1.58)	0.147 (1.69)
Tiwa Savage	0.6437 (0.5798, 0.7076)	…….	…….
Wizkid	0.6008 (0.5001, 0.6522)	…….	…….
Searches	**News**		
Davido	0.3470 (0.2512, 0.3959)	-13.226 (-2.10)	0.091 (2.33)
Burna Boy	0.1598 (0.0673, 0.2070)	-21.303 (-5.80)	0.167 (7.25)
Tiwa Savage	0.1677 (0.0750, 0.2150)	…….	…….
Wizkid	0.2514 (0.1581, 0.2990)	…….	…….
Searches	**Image**		
Davido	0.3994 (0.3130, 0.4858)	…….	…….
Burna Boy	0.1986 (0.1224, 0.2748)	-20.933 (-5.27)	0.161 (6.48)
Tiwa Savage	0.3476 (0.2594, 0.4358)	…….	…….
Wizkid	0.3472 (0.2941, 0.4647)	8.114 (1.54)	-0.074 (-2.27)
Searches	**YouTube**		
Davido	0.4129 (0.3106, 0.5152)	…….	…….
Burna Boy	0.3799 (0.2933, 0.4665)	-17.867 (-2.23)	0.149 (2.98)
Tiwa Savage	0.4307 (0.3164, 0.5450)	…….	…….
Wizkid	0.3290 (0.2237, 0.4343)	…….	…….

4. Conclusions

The present paper investigates long-range dependency and linear trend in the famosity of popular Nigerian music artists using their popularity time series datasets on Google search. This search engine is the Google Trends, which allows real time data search and historical searches. We consider weekly internet searches through Web, News, Image and YouTube searches for four artists that include Davido, Burna Boy, Tiwa Savage, and Wizkid, within the period 13.09.2015 to 6.09.2020. Our analysis approach is simple and quite understandable in music industry as it relies of persistence properties, where future time series values are expected to solely dependent on past observations. In this sense, once can easility use such observations for prediction of future observations. The initial results indicate correlations of search parameters (Web, News, Image and YouTube) of each musicians, while correlations of each search popularity parameters are weaker across musicians.

The results obtained further indicate that Web searches for these four musicians have slower tendencies to revert to mean level when compared with persistence estimates for News, Image and YouTube searches. Thus, there is persistence ups oscillations for weekly popularities of these singers based on Web searches. This is noticeable in Figure 1 which contains lesser noise compared to other three plots. While Burna Boy weekly popularity indicate positive linear trend across the four search parameters. Thus, this musician is likely to pull more online support in few years than other music youngsters.

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