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Don't Worry, Be Happy – But Only Seasonally

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Abstract: Current scientific knowledge allows us to assess the impact of socioeconomic variables on musical preferences. The research methods in these studies were psychological experiments and surveys conducted on small groups or analyzing the influence of only one or two variables at the level of the whole society. Instead inspired by the article of The Economist about February being the gloomiest month in terms of music listened to, we have created a dataset with many different variables that will allow us to create more reliable models than the previous datasets. We used the Spotify API to create a monthly dataset with average valence for 26 countries for the period from January 1, 2018, to December 1, 2019. Our study almost fully confirmed the effects of summer, December, and number of Saturdays in a month and contradicted the February effect. In the context of the index of freedom and diversity, the models do not show much consistency. The influence of GDP per capita on the valence was confirmed, while the impact of the happiness index was disproved. All models partially confirmed the influence of the music genre on the valence. Among the weather variables, two models confirmed the significance of the temperature variable. All in all, effects analyzed by us can broaden artists' knowledge of when to release new songs or support recommendation engines for streaming services.

Keywords: valence, spotify, happiness, statistical panel analysis, explainable machine learning

JEL codes: C01, C23, I31

1. Introduction

The popularity of online music via global streaming services made it possible to study the similarities and differences in musical tastes between countries, the seasonality of listening to different types of music, and the relationship between music trends and socioeconomic variables. In the beginning, we must think about the factors that influence people's music preferences. Listening to music is an inherently cultural behavior that can be shaped by users' backgrounds and contextual characteristics, which means variables in the area of economics (e.g. Gross Domestic Product – GDP) (Liu, Hu & Scheld, 2018), political issues (e.g. Freedom of Expression, Rule of Law) (Schedl, et al., 2017), or weather conditions (e.g. average temperature, season, cloud cover, or precipitation) (Lee & Lee, 2007). To go deeper into the topic, we need to understand why people are listening to music. As listening to music is a consumption, it is dictated by the desire to maximize the pleasure and minimize the pain, but in the case of music, it is not that simple. People generally tend to avoid negative emotional experiences. However, they can enjoy sadness portrayed in music and other arts (Vuoskoski et al., 2011). This paradox is called "pleasurable sadness" and its clarification has puzzled music scholars for decades (Hospers, 1969; Levinson, 1997; Scherer, 2004). Now using the data from the streaming platform, this riddle can be solved. In the previous year, the article "Data from Spotify suggest that listeners are gloomiest in February" has been published, which can be summed up in one sentence - February is the month in which we listen to the most depressive music (The Economist, 2020). The exceptions to this rule are three countries, i.e., Chile, Paraguay, and Argentina. However, this article only presents the phenomenon itself, without bringing us any closer to explanation of this phenomenon. The following research tries to not only explain what makes us listen to the least cheerful music in February, but also explore other factors influencing the choice of song by its positivity.

Musical preferences have been the subject of much sociological, psychological, and economic research. Skowron et al. (2017) showed that we can reduce the error of prediction of the popularity of genres using cultural and socioeconomic indicators such as GDP, income inequality, agriculture's share of the economy, unemployment rate, or life expectancy. Similar results have obtained Schedl et al. (2017), Liu et al. (2018). Mellander et al. (2018), whose research showed that geographic differences in music preferences reflect underlying economic and political divisions in American society. In agglomerations that are more affluent, better educated, more densely populated, and more diverse (in terms of sexual and ethnic minorities) liberal tendencies prevail people prefer sophisticated and contemporary music, while in regions, where people are less privileged, less educated, more racially homogeneous, and more religious, they tend to be conservative and prefer unpretentious and intense music. A similar pattern has been discovered at the level of states, where the authors found that the geographic structure of music preference is related to the key socioeconomic variables such as income, education, and occupation, as well as political preferences expressed as voting patterns (Rentfrow, 2013).

There are no significant differences between musical preference and any demographic variables (age, gender, ethnicity, and educational level) (Lai, 2004). Similar results were achieved by Vlegels & Lievens (2017) with a difference that people over 65 years old have a much greater interest in classical music than other groups. However, some research shows that variables as gender structure can improve the accuracy of prediction (Vigliensoni & Fujinaga, 2016; Roe, 1987).

The listening patterns can be influenced by contextual factors such as an activity the listener is involved in. Consequently, choices about listening to music can show some recurring time patterns, such as certain days of the week. Predicting the listening day of a particular genre using circular analysis was much more precise than the chance expectations (Herrera, Resa & Sordo, 2010; Baltrunas & Amatriain, 2009).

Most young people report that they use music to improve their mood, especially when they are already positive in their initial state. However, some young people reported a deteriorated mood when feeling sad or stressed. The stressed young people were more likely to listen to intense music and heavy metal, reporting no more negative impact on their mood than any other music genre (McFerran et al., 2015; McFerran, 2016). The other study shows completely another view on this topic. The results suggested that those in sad moods were not unfailingly inclined to listen to sad songs, but rather were reluctant to listen to happy songs, apparently for fear that the selection of such songs would seem inappropriate (Friedman, Gordis & Förster, 2012). Another perspective may also be taken, which suggests that musical preferences reflect mental health rather than causing it or affecting it. Some studies suggest that musical choices were related to the student's current academic success or failures, which can affect the choice of music interest (Roe, 1987; Took & Weiss, 1994). By this fact, we can say that in this area there is no scientific consensus.

Weather matters, such as the seasons or cloud cover, can define people's musical preferences, i.e., winter may sometimes isolate individuals and force them to adapt their way of travel and dress to cope with the changing weather. The research of Pettijohn and Sacco (2009) showed that more complex music, e.g., instrumental music, is preferable in winter. On the other hand, in summer preferable is dance music with an emphasis on rhythm emphasized in the genres of rap/hip-hop, soul/funk, and electronica/dance music (Rentfrow & Gosling, 2003). Application of the weather and temperature data into the recommendation system caused that evaluation of the model outperforms the comparative system that utilizes the user’s demographics and behavioral patterns only (Kim et al., 2008; Lee & Lee, 2007).

Based on the above results from the literature and the preliminary data analysis, we put forward the following hypotheses:

- Hypothesis 1: Is the effect of summer significant and has a positive effect in the model? Summertime and vacations are expected to positively influence people's mood; hence they tend to listen more happy songs.
- Hypothesis 2: Is the effect of December (Christmas) significant and has a positive effect on the valence? Christmas is a special time around the world, in this case especially considering the popularity of Christmas songs, which are full of happiness and love.
- Hypothesis 3: Will the February effect be irrelevant in the model? February is not a month with any holidays or spikes; thus, we do not expect any difference between February and other common months.
- Hypothesis 4: Will the effect of the political environment be important in the model? We assume that a high level of democratization, rule of law, civil liberties, freedom of religion, freedom of speech and artistic expression will be positively related to the level of valence. Conversely, as state corruption increases, the relationship should be negative.
- Hypothesis 5: Will the unfavorable socio-economic environment expressed by GDP per capita, and Happiness Index have a negative impact on valence? It is expected that sad music is chosen by people who are in a difficult financial situation and happy songs are listened by cheerful and peaceful people.
- Hypothesis 6: Whether the genre of music has significantly influence valence, i.e., the variables describing trends in listening will be statistically significant. In general, some music genres are happier than the others.

- Hypothesis 7a: Weather that is forcing people to stay at home negatively affects valence, i.e., the variable describing cloudiness of the sky will be significant and will have a positive impact on valence, and that the temperature will have positive impact on valence. It is expected that current music preferences are affected by the aura. Based on literature, people are more likely to listen sad music alone, than in groups of people.
- Hypothesis 7b: Weather forcing people to stay at home negatively affects valence, i.e., the variable assigning countries to specific geographical regions will be statistically significant and will have negative values for Western Europe, Northern America, Eastern Europe, Northern Europe, Southern Europe, Eastern Asia, Western Asia, and positive for Latin America and the Caribbean, Southern Europe.
- Hypothesis 8: Will the results show the effect of more Saturdays per month, i.e., the month with five Saturdays will have a positive impact on dependent variable. Saturdays are related to choosing a more positive music vibes, because people are expected to relax over the weekend and most of the parties are organized on Saturdays. Thus, difference between two months – one with four Saturdays and the other one with five Saturdays should be visible.

We believe that this article will extend past literature on this topic, by using data of aggregated choices of individuals with many variables describing current status of the country. What is more, the results can be a great advice for music business e.g., radio stations or playlist makers. They can select songs by their positivity using our analysis, which may lead to higher popularity of the radio or the playlist. The rest of this paper is organized as follows. Section 2 introduces the data set and applied models. Section 3 presents the results. Section 4 consists of a conclusion and an outlook on potential future research areas.

2. Empirical analysis

2.1 Data and variables

The earlier research on the impact of socioeconomic variables on musical preferences has been more focused on checking whether introducing new information will improve the accuracy of predicting songs that will be listened to. Whereas we are rather focused on explaining the phenomenon of trends in listening to the songs with different positivity between months and countries. We created a dataset with many variables chosen based on the knowledge gathered from the literature. We believe that this large dataset will allow to obtain more reliable model architectures than previous datasets. We used Spotify API to create the monthly average valance dataset for 26 countries for the period from 1 January 2018 to 1 December 2019. Valance describes the positivity of the song. High valence songs sound more positive (happy, cheerful, euphoric), while low valence songs sound more negative (sad, depressive, intense). To extend our dataset, we added monthly aggregated search indices from Google Trends for all the countries describing trends in music genres (i.e. rap, house, pop, rock, and classical music). To describe democratic situation of the countries we used Varieties of Democracy (V-Dem) Project (Coppedge et al., 2020). To explain how diversity of ethnic or religious groups affects selection of the songs based on positivity, we gathered data from Fractionalization research (Alesina et al., 2003).

For each country we collected 24 variables regarding socio-economic issues, weather and calendar data aggregated to the monthly level. The descriptions of these features combined with its basic statistics are summarizes in table 1. It contains the mean, standard deviation (below the mean in brackets), minimum, 25th quartile, 50th quantile, 75th quartile, and maximum. Our dependent variable ranges from 0.42 to 0.65. From quantiles and the maximum value, we may conclude that the right tail of the distribution is fat, that exhibits a left skewness and/or high kurtosis. The mean is equal to 0.4939 and is slightly higher than the median (0.487).

Table 1. Description and summary statistics for variables

Variable	Description	Mean (sd)	Min	25th Quantile	50th Quantile	75th Quantile	Max
Valence	A measure from 0 to 1 describing the musical positiveness conveyed by a track	0.4939 (0.041)	0.420	0.468	0.487	0.509	0.652
HI_score	A happiness index from World Happiness Report	6.7140 (0.72)	5.287	6.180	6.908	7.332	7.769
Gdp	A GDP per capita, resampled from quarterly to monthly	48089.61 (16391.56)	9126.600	36042.525	49640.600	58023.300	89936.300
Dancing days	A variable with a value of 1 if a given month had 5 Saturdays, and a value of 0 if it had 4 Saturdays	0.3333 (0.4718)	0.000	0.000	0.000	1.000	1.000
Ethnic_frac	An ethnic fractionalization describing probability of not belonging to the same ethnic group	0.2270 (0.1909)	0.012	0.103	0.126	0.322	0.712
Ling_frac	A linguistic fractionalization describing the probability of not belonging to the same linguistic group	0.2090 (0.1909)	0.000	0.053	0.146	0.323	0.577
Relig_frac	A religious fractionalization describing the probability of not belonging to the same religious group	0.3926 (0.2275)	0.000	0.205	0.353	0.608	0.824
Classical	A proportion of searches for classical music on YouTube to all music categories (Pop, Rock, Rap, House, Classical), download and prepared from Google Trends	0.4026 (0.2686)	0.000	0.209	0.343	0.577	1.000
Pop_music	A proportion of searches for pop music on YouTube to all music categories, download and prepared from Google Trends	0.3882 (0.2868)	0.000	0.156	0.315	0.589	1.000
Rap	A proportion of searches for rap music on YouTube to all music categories, download and prepared from Google Trends	0.4306 (0.2770)	0.000	0.205	0.399	0.622	1.000

Rock	A proportion of searches for rock music on YouTube to all music categories, download and prepared from Google Trends	0.5041 (0.2566)	0.000	0.339	0.492	0.678	1.000
House	A proportion of searches for house music on YouTube to all music categories, download and prepared from Google Trends	0.4517 (0.2716)	0.000	0.246	0.431	0.661	1.000
Sky_log	A logarithm of percent of the sky hidden behind the clouds, values from 0 to 100	3.5542 (0.3381)	0.338	3.286	3.522	3.839	4.372
Sun_hrs	A monthly sum of sunshine hours	164.2558 (80.1069)	5.000	99.000	162.050	222.750	363.000
Temperature	An average monthly temperature in Fahrenheit	53.6035 (13.99)	16.245	42.788	53.598	64.920	83.591
v2clacfree	A freedom of academic and cultural expression. Ordinal converted to interval in the original dataset.	2.2282 (1.1238)	-2.209	2.182	2.567	2.875	3.212
v2clrelig	A freedom of religion indicating to what extent individuals are free to choose and practice their religions. Ordinal converted to interval in the original dataset.	1.6816 (0.7078)	-0.661	1.398	1.726	2.090	2.800
v2x_corr	A political corruption index related to frequency of briberies and embezzlements. Interval from low to high (0-1)	0.1430 (0.1992)	0.002	0.021	0.056	0.202	0.765
v2x_polyarchy	A categorical variable indicating to what extent the electoral democracy applies in the country. Interval from low to high (0-1)	0.8156 (0.1407)	0.279	0.826	0.870	0.881	0.913
v2x_rule	A rule of law indicator, indicating independence, transparence, equality in law enforcements, and if actions of the government in line with the law. Interval from low to high (0-1)	0.8973 (0.1773)	0.201	0.891	0.968	0.987	0.999
v2xcl_disc	A freedom of discussion index indicating liberty of press and media, privilege to publicly discuss the	0.9041 (0.1646)	0.120	0.908	0.953	0.975	0.987

	political issues and liberty of academic and cultural discourse. Interval from low to high (0-1),						
v2xcl_prpty	Rights to private property. Interval from low to high (0-1)	0.9001 (0.1021)	0.422	0.908	0.930	0.942	0.971

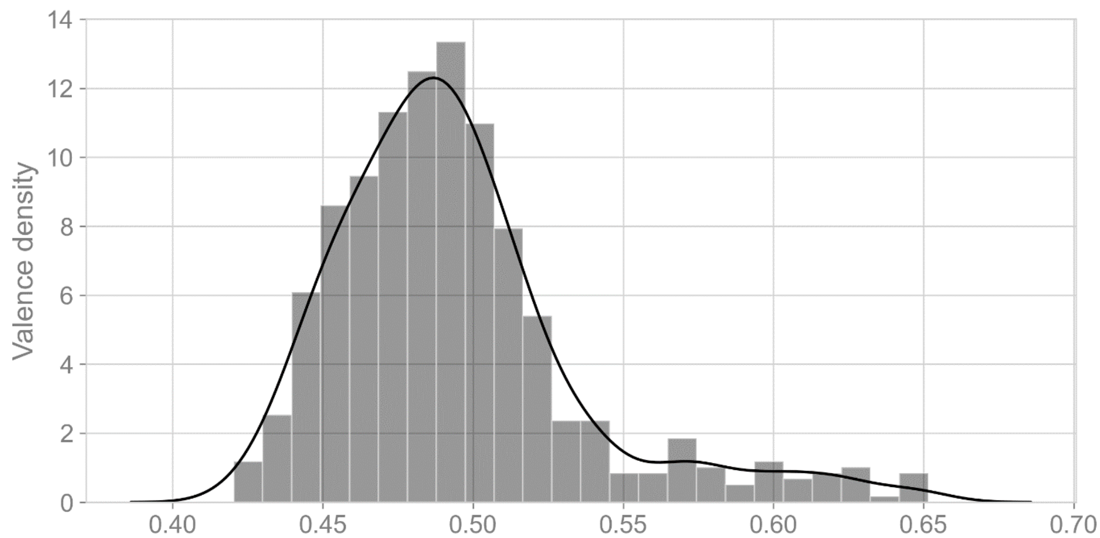
Source: Own calculations.

For S*ky*, *Temperature* and *Valence* variables, we encountered a few missing observations for Turkey and Czech Republic, which were replaced with average for country subregion group. There were few factors with yearly or quarterly frequency – GDP, Happiness index, fractional and political variables (v2) for which we replaced missing observations with last known value. Additionally, we used min-max scaler for trends in music genres.

One variable, *Subregion,* which assigns a country to a given region, was not described in the table due to its categorical character. We identified 8 regions, i.e. Western Europe (6 countries), Northern America (Canada and USA), Eastern Europe (4 countries), Northern Europe (7 countries), Southern Europe (4 countries), Eastern Asia (Japan), Latin America and the Caribbean (Mexico), and Western Asia (Turkey).

Probability density function of Valence has been estimated using Kernel Density Estimate (KDE). The estimation results along with the histogram are presented in figure 1. Its fragment, i.e., from 0.40 to 0.55, resembles the normal distribution. However, the right tail is fat. To understand where the reasons behind this phenomenon the valence values above 0.55 were analyzed. There were 53 observations, so almost 10% of the sample. Most of the records come from Spain and Mexico. Importantly, all 24-month observations for Mexico exceeded this threshold, and in case of Spain almost all - 21 out of 24 observations. In addition, six observations come from Japan and two from Finland.

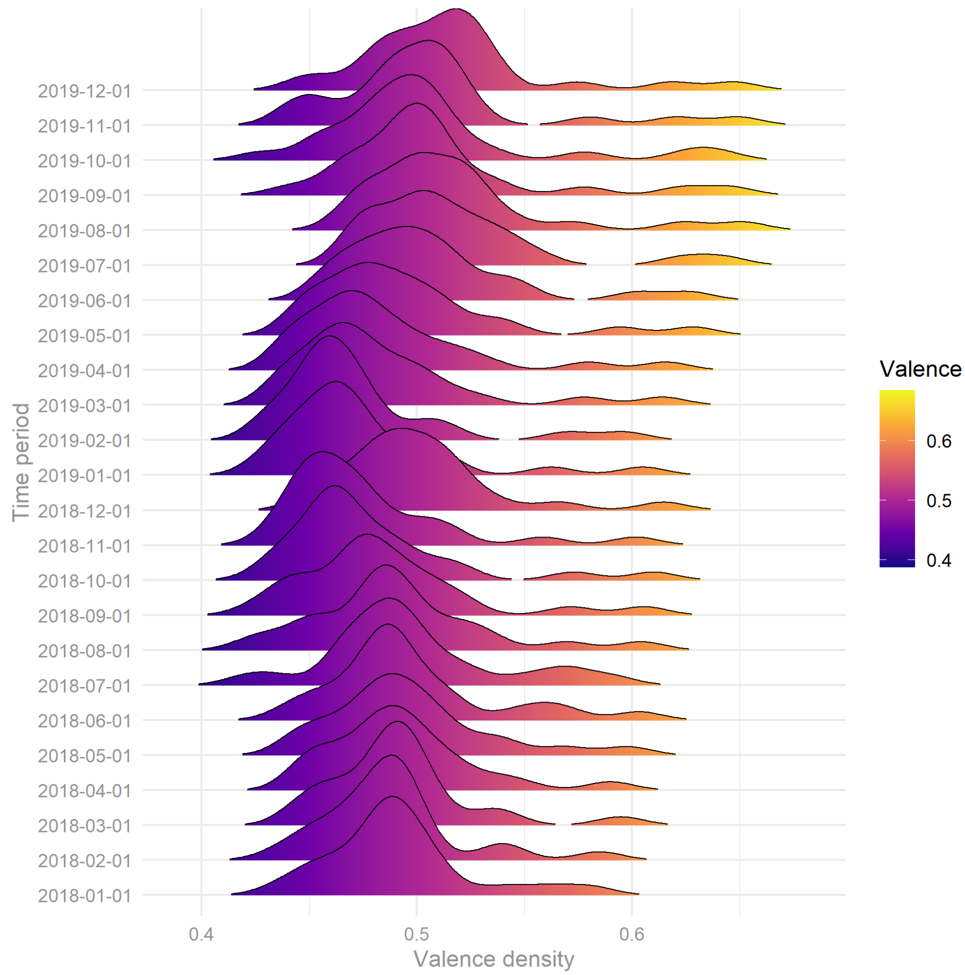
Figure 1. Kernel Density Estimate (KDE) plot with histogram for Valence



Source: Own calculations.

Figure 2 shows how valence changes over time. December stands out here for both years. Therefore, we can expect the hypothesis for this effect to be confirmed. For 2019, the summer effect may be noticeable, but for 2018 it is not very visible. What is more, from figure 2. analysis we cannot see that February stands out with lower valence. As it has similar levels to nearest months – January and March.

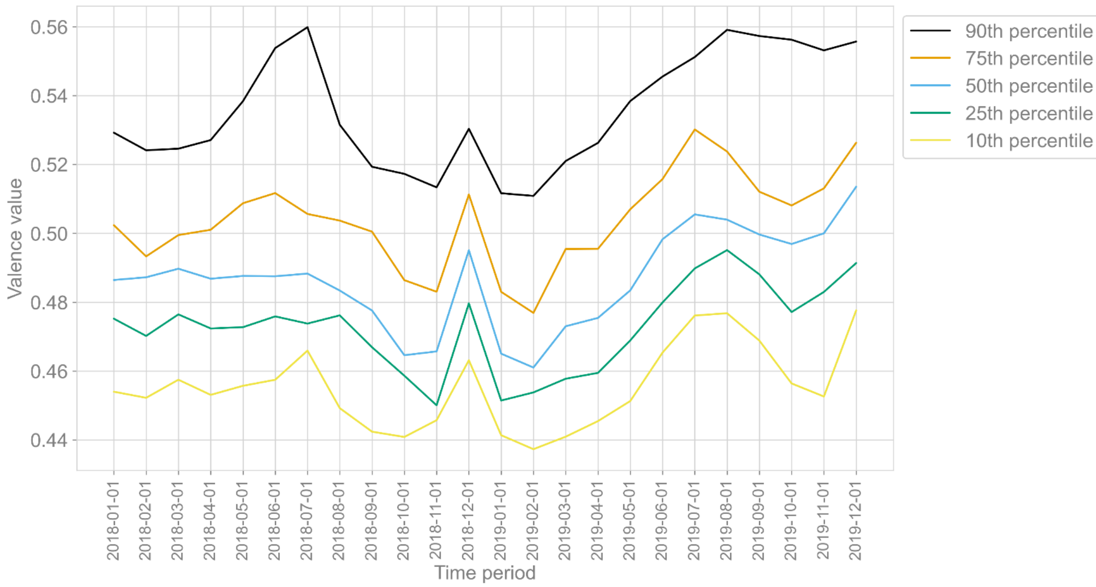
Figure 2. Valence probability density over the time segregated from the most recent (at the top) to the oldest (at the bottom)



Source: Own calculations.

Figure 3 shows how the values of valence percentiles change over time. Here, the December effect is also clearly visible, which is interesting that it appears not only on the average level but also applies to every percentile. The summer effect (July and August) is clearly visible, although what we have expected earlier, the effect is much more visible for 2019. In 2018, the effect was observable only for the 90th percentile. Thus, countries that listen to happy music for most of the time in the year, are listening to even happier music in summer in comparison to other countries.

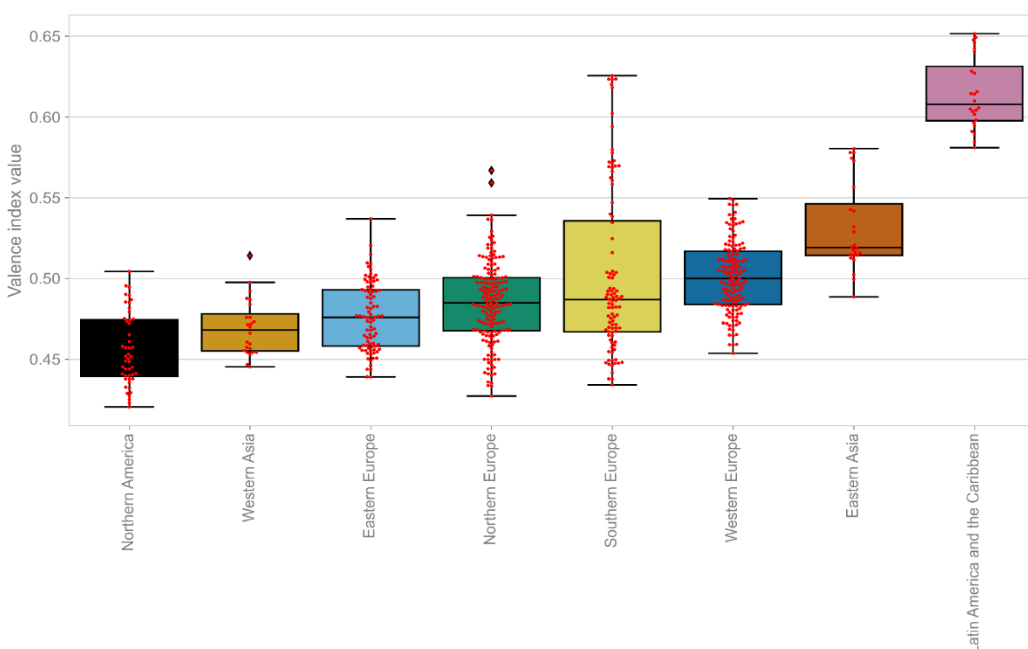
Figure 3. Quantile trend plot for Valence



Source: Own calculations.

Figure 4 shows the valence in individual regions. Southern Europe, Latin America and the Caribbean stand out clearly from other regions. In both regions, Spotify users listen to much more positive music.

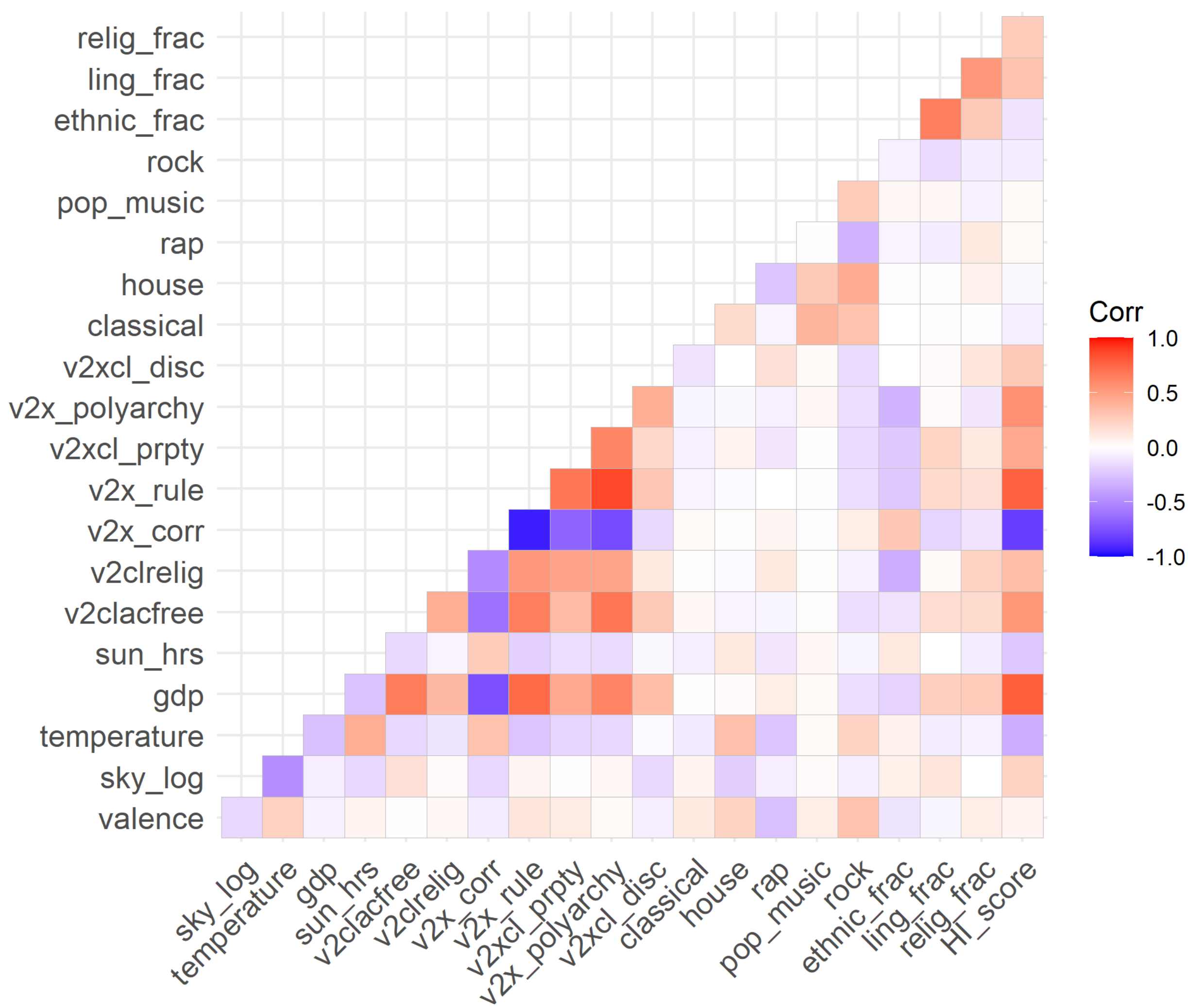
Figure 4. Valence in particular subregions



Source: Own calculations.

Figure 5 shows the correlation between the variables. The most closely related variables are the political variables, i.e. *v2clacfree, v2clrelig, v2x_corr, v2x_rule, v2xcl_prpty, v2c_polyarchy, and v2xcl_disc*. The correlation between valence and the explanatory variables can be assessed as moderate (it ranges from 0.2 to 0.5).

Figure 5. Correlation between the variables used in the research



Source: Own calculations.

2.2 Empirical design

2.2.1 Panel Data Regression Model

The data used in this research is a panel with 26 countries serving as groups and 24 monthly observations for each variable, hence the most obvious choices are panel data regression models with fixed effects and random effects. For the purpose of determining the proper estimator, we used the Hausman test which null hypothesis points towards using a random effects estimator and the alternative hypothesis indicates that the random effects estimates are inconsistent and hence fixed effects estimator should be chosen. The results of the Hausman test indicated that the null hypothesis is rejected, and hence the fixed effects (FE) panel regression should be used. In order to come up with a set of significant variables for regression analysis we applied General-to-Specific modelling procedure (Campos, Ericsson & Hendry, 2005), which consists of iterative model estimation, dropping the variable with the highest p-value of the significance test and testing the joint hypothesis of insignificance of the dropped variables.

2.2.2 Dynamic Panel Data Regression Model

Dynamic panel data regression models are used in cases where the autoregressive process of the dependent variable is significant, hence its future values depend on the past. To test this assumption we tested significance of AR(1) process of the dependent variable. The results strongly rejected the null hypothesis of insignificance and hence indicated that the autoregressive term is not redundant in explaining the regressand. Therefore, we concluded that it is necessary to include the lagged values of the dependent variable in the panel. The rationale behind this model is also the retention in music taste and the fact that people generally tend to listen a specific type of music for a longer period as well as come back to the songs they enjoyed listening recently. In such case using fixed effects regression model will lead to the Nickell's bias and the estimated coefficients will be inaccurate, especially in the context of panels with small T and large N. This bias arises due to exclusion of individual fixed effect from each observation, which in case of including the lagged regressor leads to introducing correlation between the regressors and the error term. Since the panel used in this research is relatively short, as it consists of only 24 monthly observations, we have decided to use Arellano and Bover / Blundell and Bond system estimator, which is unbiased and effective for dynamic panel data even in a small sample. Consistently with previous panel regression model, General-to-Specific modelling approach was applied to select the set of significant variables.

2.2.3 CatBoost model and Explainable Artificial Intelligence

To analyze the research problem in depth, we also applied the CatBoost model (Prokhorenkova et al., 2017) in its classic regression form. That is, we entered panel data into the model, and the machine learning estimator treats them as cross-sectional data. Importantly, we have chosen not to consider the specificity of the time series in this model in order to simplify the estimation and statistical inference process.

The biggest advantage of the boosting trees model in our context is a lack of assumption regarding the linear function, thus it can handle highly non-linear interactions in the data. We are aware that manual search for an appropriate polynomial or power functional form for the linear panel approach like fixed-effects model usually fails due to a vast space of possible solutions. What is more, boosting schemes applied in CatBoost allowed us to control variance (overfitting) in a responsible way. In addition, CatBoost perfectly model highly cardinal variables (we have such in the analysis). Importantly, the CatBoost model interpretation is not as trivial as for FE or DPD.

However, it is feasible with techniques such as feature importance and feature effects powered by SHapley Additive exPlanations (Lundberg & Lee, 2017).

Our CatBoost modelling process was relatively straightforward. We searched for the best hyperparameters in a 5-folded cross-validation grid search with following setup (based on our experience): depth [2, 3, 4, 5, 6, 7], learning rate [0.01, 0.05, 0.1, 0.25, 0.5], iterations [50, 100, 150, 200, 250, 300]. During this process, our evaluation metric was root mean squared error.

Feature importance techniques enable us to analyze the significance of a given variable throughout the model and determine its quasi-participation in the predictive power of the model. SHapley Additive exPlanations (SHAP) is a game theoretic approach to explain the output of any machine learning model. As we were focused on summarizing the effects of all the features, we used SHAP summary plot. It sorts features by the sum of SHAP value magnitudes over all samples and uses SHAP values to show the distribution of the impact each feature has on the model output. The color represents the feature value (red for high, blue for low). What is more, we used SHAP Partial Dependence Plot (2D partial Partial Dependence Plot) to examine the overall effect of a single feature (of two features) across the whole dataset. This kind of plots represents a change in dependent variable as independent variable changes.

3. Results

3.1 Fixed effects panel model

After conducting General-to-Specific approach, the finally obtained model for fixed effects has 11 independent variables, 10 of the variables are significant at the level of at least 0.1 and 8 of them are significant at the level of at least 0.05. The values of coefficients, standard errors, and p-value are reported in the table 2.

Table 2. Coefficients, standard errors, and p-value for Panel Data Regression Models

Variable	Model 1	Model 2	Model 3
Temperature	0.0002 (0.0002)	0.00012 (0.0001)	-
Gdp	0.000003* (1.14e-06)	0.000003* (1.16e-06)	0.000003* (1.12e-06)
HI_score	-0.03021 (0.019)	-0.02816 (0.0191)	-0.033 (0.0197).
V2clrelig	0.01314* (0.0063)	0.0139* (0.0058)	0.014854* (0.006)
V2x_corr	-0.35842*** (0.0466)	-0.33093*** (0.0559)	-0.33766*** (0.0556)
V2xcl_prpty	0.13198 (0.0975)	-	-
Classical	0.00675 (0.0037).	0.00733 (0.0039).	0.00636 (0.00397)
House	0.00016*** (0.0032)	0.011896*** (0.00316)	0.01355*** (0.0031)
Rap	-0.01212*** (0.0041)	-0.01446*** (0.00379)	-0.01586*** (0.00343)
Pop_music	0.0068129 (0.0045155)	0.0078 (0.00459).	0.008 (0.0048).
Dancing_days	0.00381*** (0.0005)	0.00376*** (0.0005)	0.00435*** (0.00055)
Summer	0.00787*** (0.00124)	0.00804*** (0.00127)	0.0104*** (0.00169)
Xmas	0.01584*** (0.0035)	0.015869*** (0.00346)	0.0139*** (0.00344)

Source: Own calculations.

This model strongly confirms the hypotheses 1, 2, and 3 about the importance of the summer and December effects and not significant February effect. Hypothesis 4 has been partially confirmed. Only variables regarding freedom of religion (*v2clrelig*) and political corruption (*v2x_corr*) are statistically significant. Hypothesis 5 has been confirmed. Variable *gdp* is significant and is positive, but surprisingly *HI_score* is not significant. It may be caused by correlation between *HI_score* and *gdp*. Hypothesis 6 has been partially confirmed. The impact of the house, rap, and pop has been confirmed. For the house and pop music effects are positive, while for rap it is negative. Hypotheses 7a and 7b have been fully rejected. The variables *temperature* and *sky* are not statistically significant. Hypothesis 8 has been confirmed. The variable *dancing_days* is significant and positive.

3.2 Arellano and Bover / Blundell and Bond system estimator

Table 3. Coefficients, standard errors, and p-values for Arellano and Bover / Blundell and Bond system estimator

Variable	Model 1 A-B / B-B	Model 2 A-B / B-B	Final model A-B / B-B
Lag.Valence	0.6280*** (0.0276)	0.632*** (0.027)	0.623*** (0.0264)
Temperature	0.00038*** (0.000055)	0.0004*** (0.00004)	0.00036*** (0.0004)
Gdp	-7.90 e-07*** (3.13 e-07)	-7.69 e-07** (3.14 e-07)	-7.61 e-07** (3.31 e-07)
HI_score	0.0232*** (0.0056)	0.023*** (0.0056)	0.0225*** (0.0056)
V2clrelig	0.0139*** (0.0033)	0.0135*** (0.0034)	0.01425*** (0.0.033)
V2x_polyarchy	0.1511*** (0.0421)	0.15*** (0.042)	0.1495*** (0.0422)
V2xcl_disc	-0.1810*** (0.035)	-0.178*** (0.035)	-0.1795 (0.035)
Log_sky	0.0041 (0.0037)	0.004 (0.03)	-
House	0.0071*** (0.0.018)	0.007*** (0.0018)	0.0071*** (0.0018)
Rap	-0.0028* (0.0018)	-0.0029* (0.0019)	-0.0032** (0.0018)
Pop_music	0.00921*** (0.0017)	0.0091*** (0.0017)	0.0094*** (0.0017)
Dancing_days	0.0047*** (0.00077)	0.0046*** (0.00078)	0.0045*** (0.0007)
Summer	0.0011 (0.0011)	-	-
Xmas	0.022*** (0.0014)	0.022*** (0.0014)	0.022*** (0.001)
Sun_hours	0.000024*** (0.0000065)	0.000023*** (0.0000065)	0.00002*** (0.0000068)

Ethnic_fraction	0.1546*** (0.0253)	0.1545*** (0.0254)	0.1578*** (0.0253)
Lingual_fraction	-0.228*** (0.03599)	-0.227*** (0.036)	-0.228*** (0.218)
Relig_fraction	0.089*** (0.0212)	0.088*** (0.022)	0.087*** (0.0218)

Source: Own calculations.

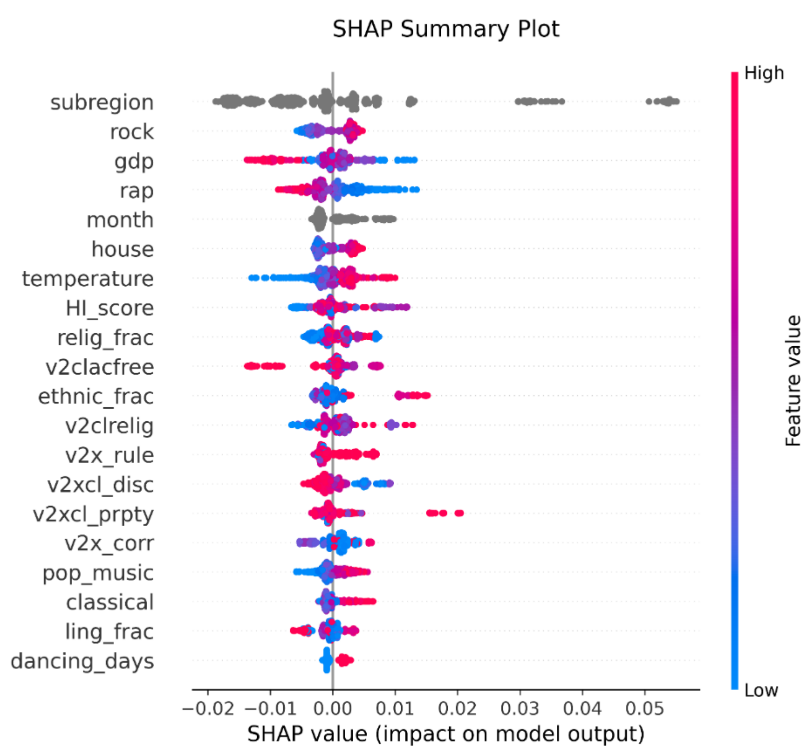
In table 3. we presented the results from Arellano and Bover / Blundell and Bond system estimator on dynamic panel data. In the table we showed the only last three iterations of General-to-Specific approach. All independent variables were significant at 5% level of confidence in our final model. The autoregressive process was significant, which confirms the usage of Dynamic Panel Data estimators. Retention rate is almost 63% for valence. Temperature and number of sun hours has positive impact on valence, which confirms the 7th hypothesis that the bad weather forces people to stay at home, which can lead to lower valence levels. In contradiction to the FE model, GDP has negative impact on valence. In countries with favorable political environment (*v2clrelig*, *v2x_polarchy*) we can expect higher valence. Variables describing trends of music genre are also statistically significant for house, rap and pop music. Only rap music has negative impact on valence, which is in line with intuition that rap music tends to be negative. Number of Saturdays in a month has a positive impact on dependent variable, which suggest that Saturday itself has significant impact. Next, we wanted to check, if the second and the third hypotheses were confirmed. February dummy was insignificant, which confirms third hypothesis. We also observed a positive significant impact of Christmas dummy, however variable flagging summer was insignificant.

To confirm the proper selection of the instruments, we calculated Arellano-Bond test. Test confirms proper form of the model, as we expected the autocorrelation of first order – the test rejects the null hypothesis for zero autocorrelation in first-differenced error and for second order we cannot reject null hypothesis at 5% level of confidence (p-value is equal to 0.861).

3.3 CatBoost model

Our final CatBoost model gathered 22 explanatory variables. Based on cross-validation (described in the methodology subsection), we set following hyperparameters values: iteration 250, learning rate 0.1 and tree depth 3. The general results of the model obtained using SHAP Summary Plot are presented in the figure 6. It clearly shows that variables like subregion, rock, GDP, rap, month of the year, house and temperature are the most important for this discriminative model. We see that variables generally affect model's output in expected way. But to be more specific, we propose to analyze SHAP Partial Dependence Plots for exogenous features. These plots are visualized in the figure 7 (note the different scale of the ordinate axis).

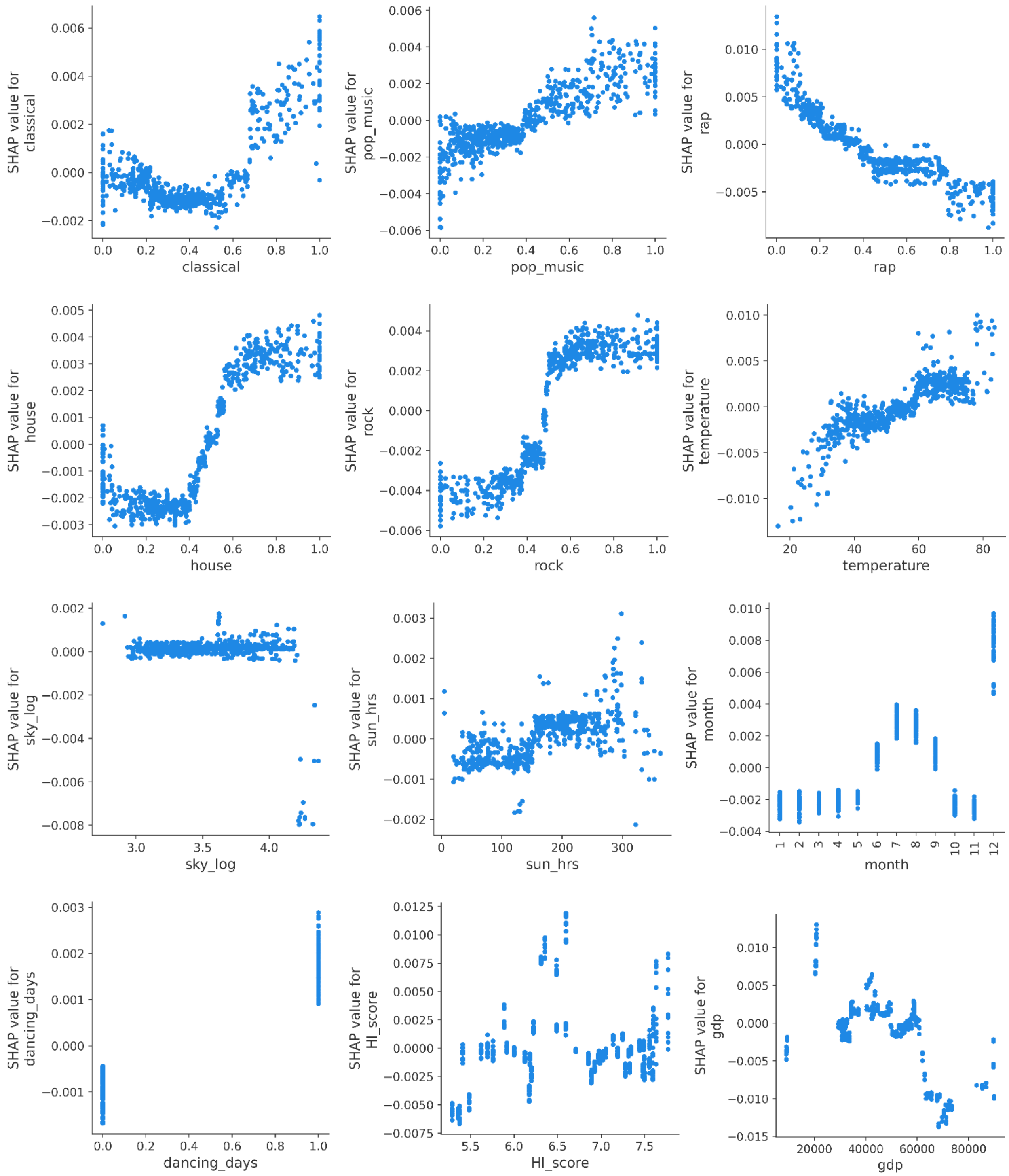
Figure 6. SHAP Summary Plot based on CatBoost model

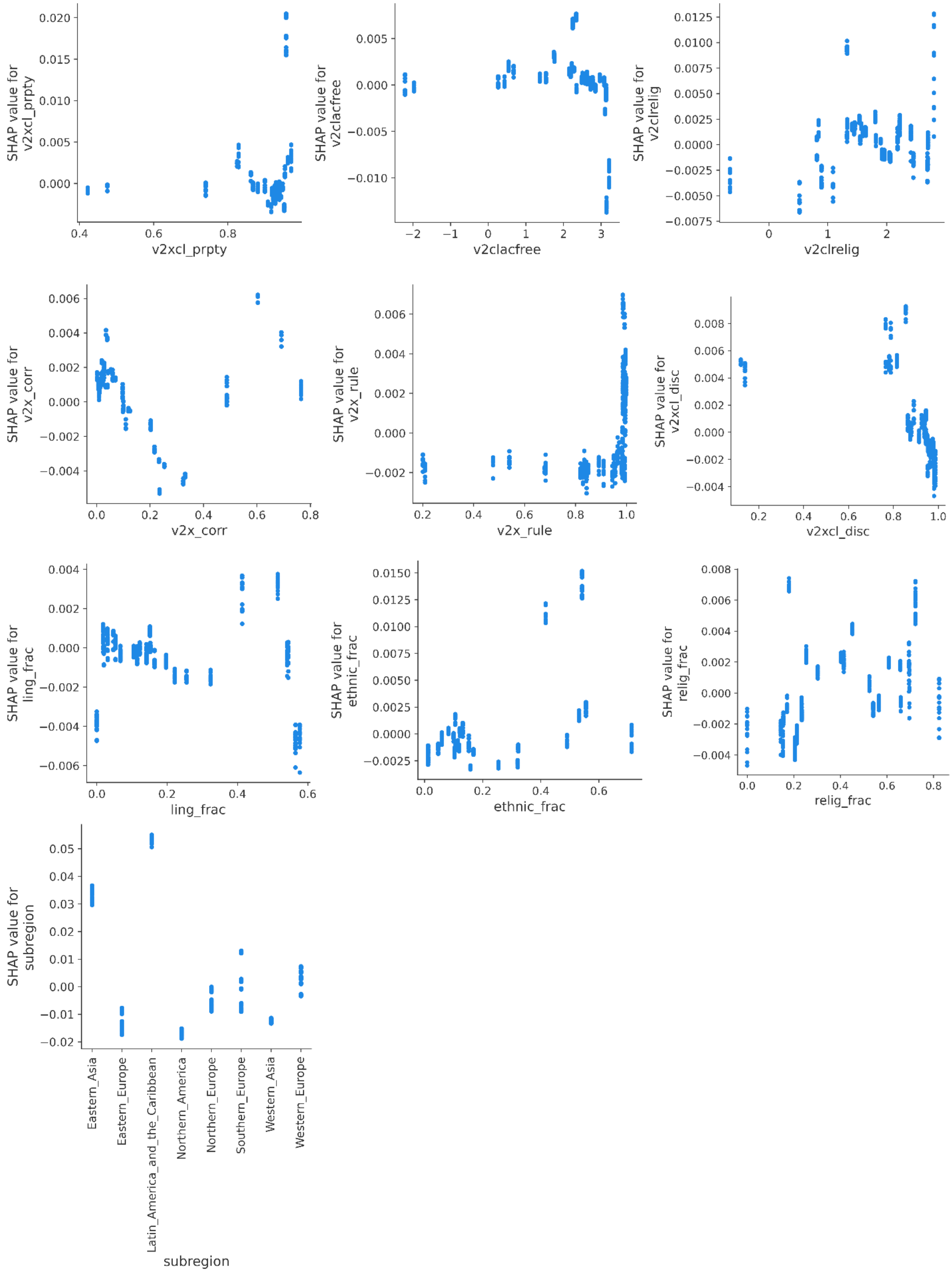


Source: Own calculations.

Let us first analyze the influence of music genres. We can easily conclude that the greater popularity of pop, house, rock in each country, the greater the valence. The effect of rap is strictly negative, while the popularity of classical music only has a measurable positive effect on the expected value of the target variable from a certain point onwards. In the case of meteorological variables, temperature has a clearly monotonic positive effect on valence, and the logarithmical cloudiness of the sky is not relevant to the model at all. The effect of sunshine hours seems to be positively significant only for the extreme values of this exogenous variable. For the months, valence is positively influenced by the holiday period (June to September) and Christmas (December). The impact of other months is insignificant. Dancing days have a positive impact on the target variable. The impact of the Happiness index is unclear. An interesting finding is that countries with low and medium GDP per capita have higher expected valence than the richest countries. Jointly, the political and constitutional variables do not clearly indicate their impact on the explanatory variable. However, the rule of law, rights to private property, and freedom of religion have a very positive influence on the outcome of the model. An interesting effect has the freedom of discussion index, which for the largest value has a negative effect on the fitted value from the model. The higher the religious and ethnic diversity, the more we expect the valence to be positively affected. Linguistic diversity to some extent suggests a similar relationship. The subregion variable is hard to interpret due to its poor balancing, while it shows that subregions are strongly homogeneous with respect to the target variable.

Figure 7. SHAP Partial Dependence Plots based on CatBoost model

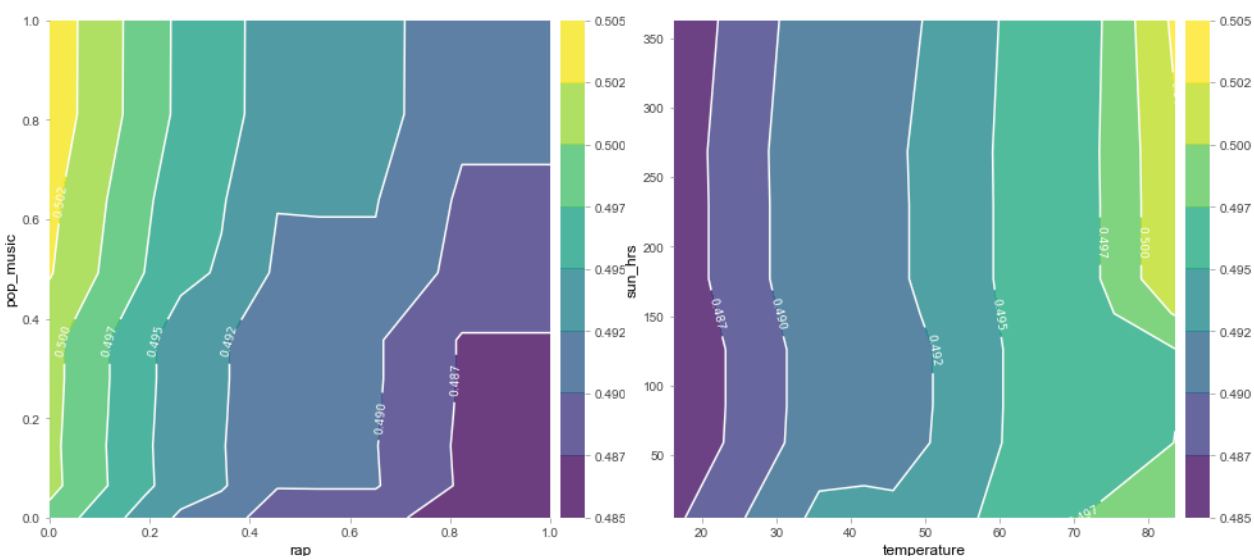


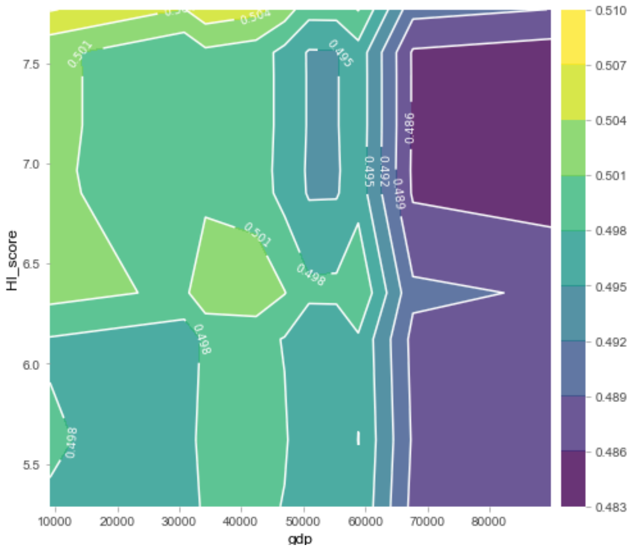


Source: Own calculations.

In addition, we used SHAP 2D Partial dependence plots to interpret the CatBoost results (see figure 8). In this case, the pairs of variables of our interest are *pop_music – rap*, *sun_hours – temperature* and *HI_score - gdp*. We decided to test the main effect of each feature and their interaction effect. Based on these graphs, we can confirm the earlier conclusions of the 1D PDP, i.e. the popularity of rap has a negative effect on valence, while pop has a positive effect. Altogether we can see that even a relatively low popularity of rap, with a high popularity of pop strongly negatively affects the final valence. When it comes to the relationship between temperature and days of sunshine, temperature is clearly the key. Sunny days create a bulge in the graph, i.e. despite high temperature, few sunny days will lower the expected value of the target variable. A very interesting relationship is shown by the Happiness Index and GDP. It turns out that the highest expected valence is in countries with relatively low income and high Happiness Index. Moreover, moderate Happiness Index and average GDP also lead to above average valence.

Figure 8. SHAP 2D Partial Dependence Plots based on CatBoost model





Source: Own calculations.

To sum up, the two models fully confirmed the hypothesis 1, 2 and 3. Only the Dynamic Panel Data Regression Model did not confirm the summer effect. In the context of hypothesis 4, all models confirmed the significance of freedom to religion (*v2clrelig*). Two models confirmed the significance of the political corruption index (*v2x_corr*), the electoral democracy (*v2c_polyarchy*), religious diversity (*relig_frac*) and ethnic diversity (*ethnic_frac*). Hypothesis 5 for *gdp* was confirmed, although this variable had the opposite effect to that predicted. For the Dynamic Panel Data Regression Model and CatBoost, it was negative, for the fixed effects model the *gdp* impact is positive. All models partially confirmed hypothesis 6. House and pop had a positive effect on the valence, while the rap negative. Only the CatBoost model confirmed the added impact of rock. All models refuted hypotheses 7a with regard to the significance of cloud cover (*sky_log*). In case of hypothesis 7b subregions were strongly significant only for CatBoost model (it can utilize very well highly cardinal variables). All models confirmed the significance and a positive coefficient for the variable *dancing_days,* which confirmed the last hypothesis 8.

4. Conclusions

The models allowed to confirm most of the hypotheses put forward at the beginning. These results are important as much as they contradicted the conclusions drawn by The Economist that February would be the gloomiest month in terms of the music listened to. The remaining effects may broaden the artists' knowledge of when to release new songs. Streaming services such as Spotify may be another beneficiary of the results. The recommendation engines for songs and playlists could be more accurate if they also considered the variables we added.

The first limitation of this study is that valence may be largely related to the kinds of music. Therefore, further research should focus on the analysis of disaggregated data and a possible valence comparison for given genres of music. The distribution of valence at the country level could also be interesting. The analysis of the mean alone does not provide all information about the mood of the music being listened to, there is a possibility that distribution can be bimodal – people can listen to extremely negative and extremely positive music. Additionally, the influence of political variables is unclear. There is no theoretical basis for the interpretation of the obtained results based on theories from the literature. Another limitation is the short period of the analyzed data. Two years do not allow to properly capture the seasonality, which was our main interest in the third hypothesis. Another limitation is the lack of monthly macroeconomic and social data. For this reason, some of the variables in our analysis had only two unique values.

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