THE INFLUENCE OF MACRO- AND SOCIO-ECONOMIC FACTORS ON THE CONSUMPTION OF MUSIC THROUGHOUT THE YEAR

Szymon Lis https://orcid.org/0000-0001-9878-3856
Mateusz Kijewski
Michał Woźniak https://orcid.org/0000-0001-7313-864X
Maciej Wysocki https://orcid.org/0000-0002-1693-1438
Faculty of Economic Sciences
University of Warsaw, Poland
e-mail: sm.lis@student.uw.edu.pl;
mj.kijewski@student.uw.edu.pl;
mj.wozniak9@student.uw.edu.pl;
m.wysocki9@student.uw.edu.pl

Abstract: Popular research methods in assessing the impact of macroeconomic and environmental variables on music preferences were psychological experiments and surveys with small groups or analyzing the effect of one or two variables in the whole population. 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 variables. We used Spotify API to create a dataset with average valence for 26 countries for the period from January 1, 2018, to December 1, 2019. Then we applied the regression and machine learning models to them. Our study confirmed the effects of summer, December, and the number of Saturdays in a month and contradicted the February effect. 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. Macroeconomic variables turned out to have non-linear relationships that made interpretations difficult, while the environmental ones clearly indicated a linear relationship with valence.

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

JEL classification: C01, C23, I31

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. Due to this availability, we are able to investigate what has a more significant relationship with music preferences - macroeconomic variables or the generally understood environment, which is less abstract than for example GDP. 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 et al. 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, at the same time focusing on the aspect of a special distinction between macroeconomic and environmental variables.

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]. This is a condensed description of how macroeconomic variables affect the music we listen to.

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 et all. 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 et al. 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, 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].

It is not only macroeconomic variables that influence musical taste. These are also factors that we refer to as environmental ones - such as the weather, the current mood, or the season of the year.

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 and by applying machine learning model, that was never used before in this area 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.

EMPIRICAL ANALYSIS

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 and maximum. Our dependent variable ranges from 0.42 to 0.65. From quantiles (omitted in table report) 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 with its type

Variable (type of variable – macroeconomic / environment)	Description	Mean (sd)	Min	Max
Valence (target variable)	A measure from 0 to 1 describing the musical positiveness conveyed by a track	0.4939 (0.041)	0.420	0.652
HI_score (macroeconomic)	A happiness index from World Happiness Report	6.7140 (0.72)	5.287	7.769
Gdp (macroeconomic)	A GDP per capita, resampled from quarterly to monthly	48089.61 (16391.56)	9126.600	89936.300
Dancing days (environment)	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	1.000
Ethnic_frac (environment)	An ethnic fractionalization describing probability of not belonging to the same ethnic group	0.2270 (0.1909)	0.012	0.712
Ling_frac (environment)	A linguistic fractionalization describing the probability of not belonging to the same linguistic group	0.2090 (0.1909)	0.000	0.577
Relig_frac (environment)	A religious fractionalization describing the probability of not belonging to the same religious group	0.3926 (0.2275)	0.000	0.824
Classical (environment)	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	1.000
Pop_music (environment)	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	1.000
Rap (environment)	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	1.000
Rock (environment)	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	1.000
House (environment)	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	1.000
Sky_log (environment)	A logarithm of percent of the sky hidden behind the clouds, values from 0 to 100	3.5542 (0.3381)	0.338	4.372
Sun_hrs (environment)	A monthly sum of sunshine hours	164.2558 (80.1069)	5.000	363.000
Temperature (environment)	An average monthly temperature in Fahrenheit	53.6035 (13.99)	16.245	83.591

| Variable (type of variable – macroeconomic / environment)	Description	Mean (sd)	Min	Max
v2clacfree (macroeconomic)	A freedom of academic and cultural expression. Ordinal converted to interval in the original dataset.	2.2282 (1.1238)	-2.209	3.212
v2clrelig (macroeconomic)	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	2.800
v2x_corr (macroeconomic)	A political corruption index related to frequency of briberies and embezzlements. Interval from low to high (0-1)	0.1430 (0.1992)	0.002	0.765
v2x_polyarchy (macroeconomic)	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	0.913
v2x_rule (macroeconomic)	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	0.999
v2xcl_disc (macroeconomic)	A freedom of discussion index indicating liberty of press and media, privilege to publicly discuss the political issues and liberty of academic and cultural discourse. Interval from low to high (0-1),	0.9041 (0.1646)	0.120	0.987
v2xcl_prpty (macroeconomic)	Rights to private property. Interval from low to high (0-1)	0.9001 (0.1021)	0.422	0.971

Source: own calculations

For Sky, 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
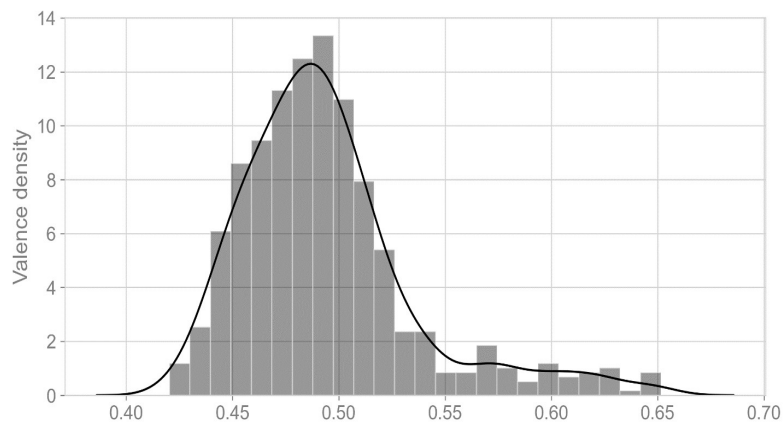
Source: own calculations

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)
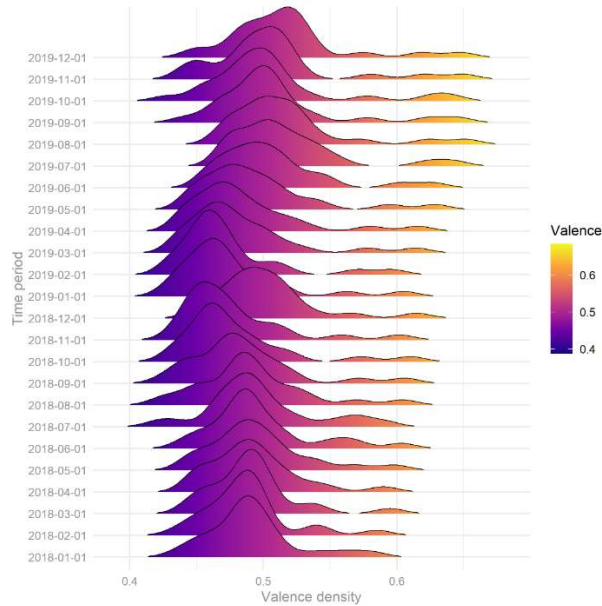
Source: own calculations

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.
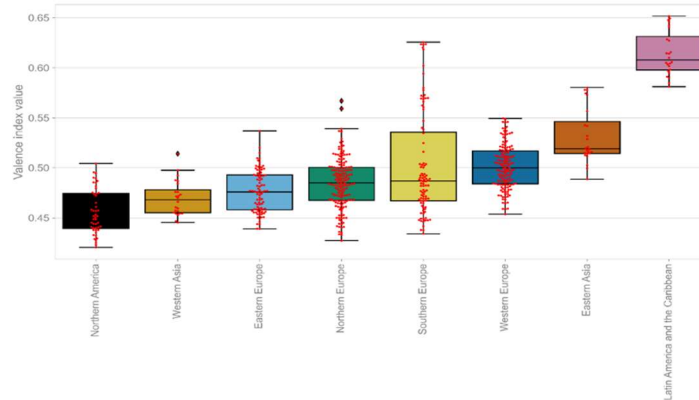
Figure 3. Quantile trend plot for Valence
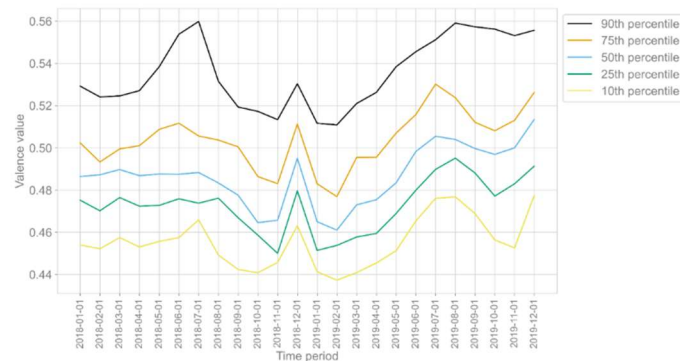
Source: own calculations

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
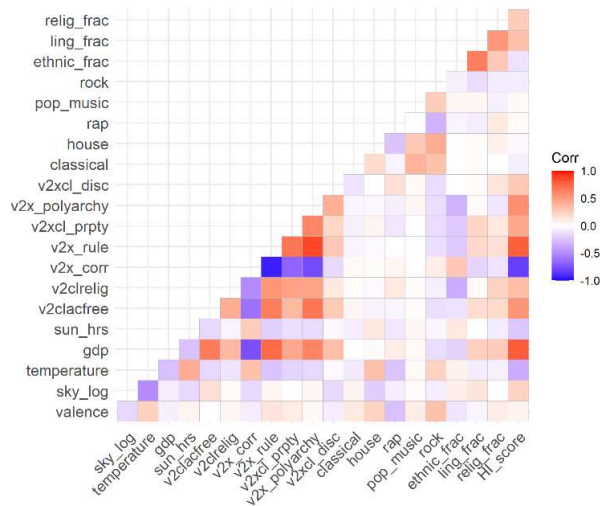
Source: own calculations

EMPIRICAL DESIGN

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 et al. 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.

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.

It is important to note that the General-to-Specific modelling procedure used in the panel data regression and dynamic panel data regression models is preferred over stepwise regression for variable selection. Stepwise regression (Efroymson, 1960) is a popular method for model selection, but it suffers from a number of

drawbacks. One of the main issues with stepwise regression is that it can lead to overfitting, especially when the number of predictors is large relative to the sample size. This occurs because stepwise regression selects variables based on their individual contribution to the model fit, without considering their joint effects. Furthermore, stepwise regression can produce unstable and inconsistent models. The selected variables and their coefficients may vary substantially depending on the order in which they are entered into the model, and small changes in the data can lead to large changes in the selected variables. Additionally, stepwise regression assumes that the predictor variables are independent, which is often not the case in real-world data. In contrast, the General-to-Specific modelling procedure used in this research starts with a full model containing all potential predictors, and then iteratively removes non-significant variables based on a joint hypothesis test. This approach ensures that the selected variables are statistically significant and have a meaningful joint effect on the dependent variable. It also reduces the risk of overfitting and produces more stable models. Therefore, it is recommended to use General-to-Specific modelling instead of stepwise regression for variable selection in regression analysis.

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.

RESULTS

Fixed effects panel model

After applying the General-to-Specific approach to the dataset, we obtained the final fixed effects model (model 3) which includes 11 independent variables. Of these, 10 variables are statistically significant at the level of at least 0.1, and 8 of them are significant at the level of at least 0.05. The coefficients, standard errors, and p-values for each variable in the final model are reported in Table 2. It is important to note that the approach involved several iterations before the final model was obtained. In Table 2, we present the results of the last three iterations of the General-to-Specific approach, which include model 1, model 2, and the final model 3.

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)
m	-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)

Variable	Model 1	Model 2	Model 3
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.

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)

Variable	Model 1 A-B / B-B	Model 2 A-B / B-B	Final model A-B / B-B
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

Table 3 presents the results obtained from the Arellano and Bover/Blundell and Bond system estimator on dynamic panel data. The General-to-Specific approach was used to select the final model, and in Table 3, we present the results of the last three iterations of this approach, which include model 1, model 2, and the final model 3. 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).

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
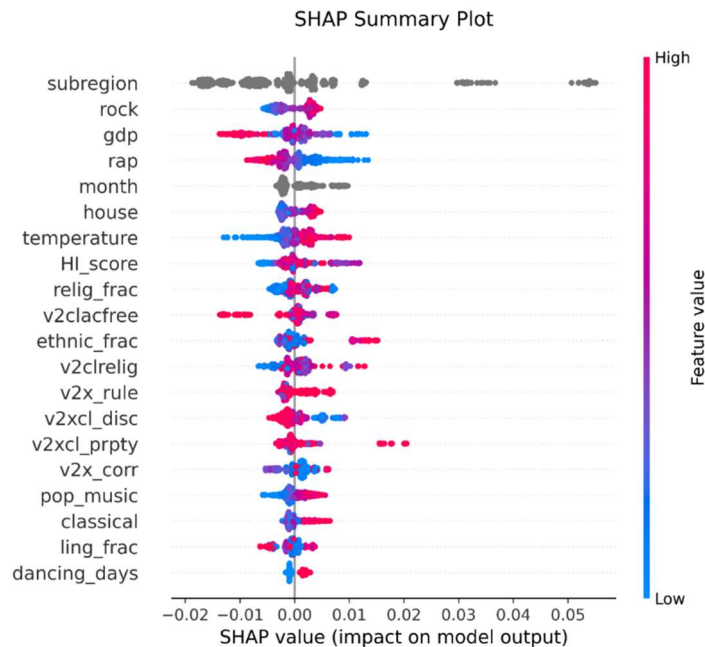
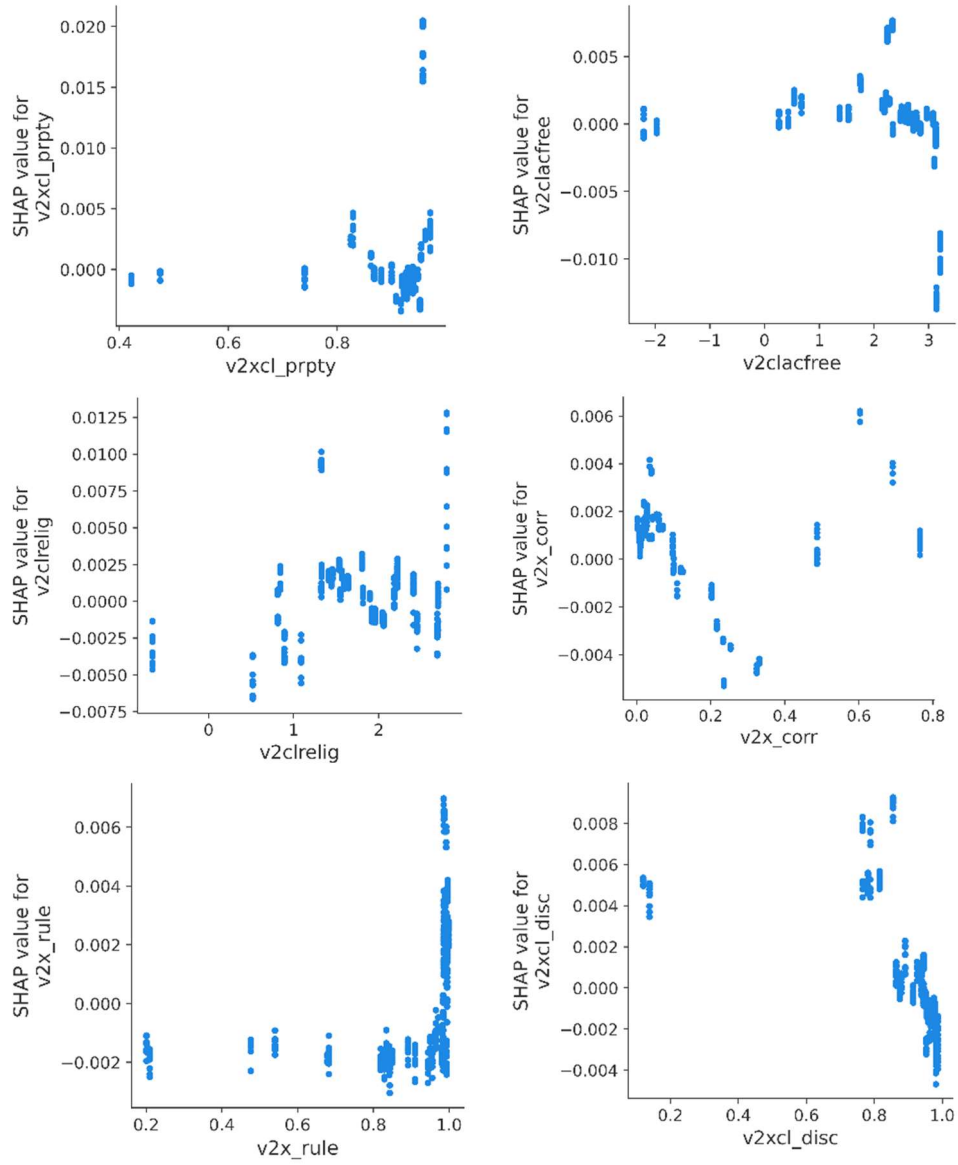Source: own calculations

      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
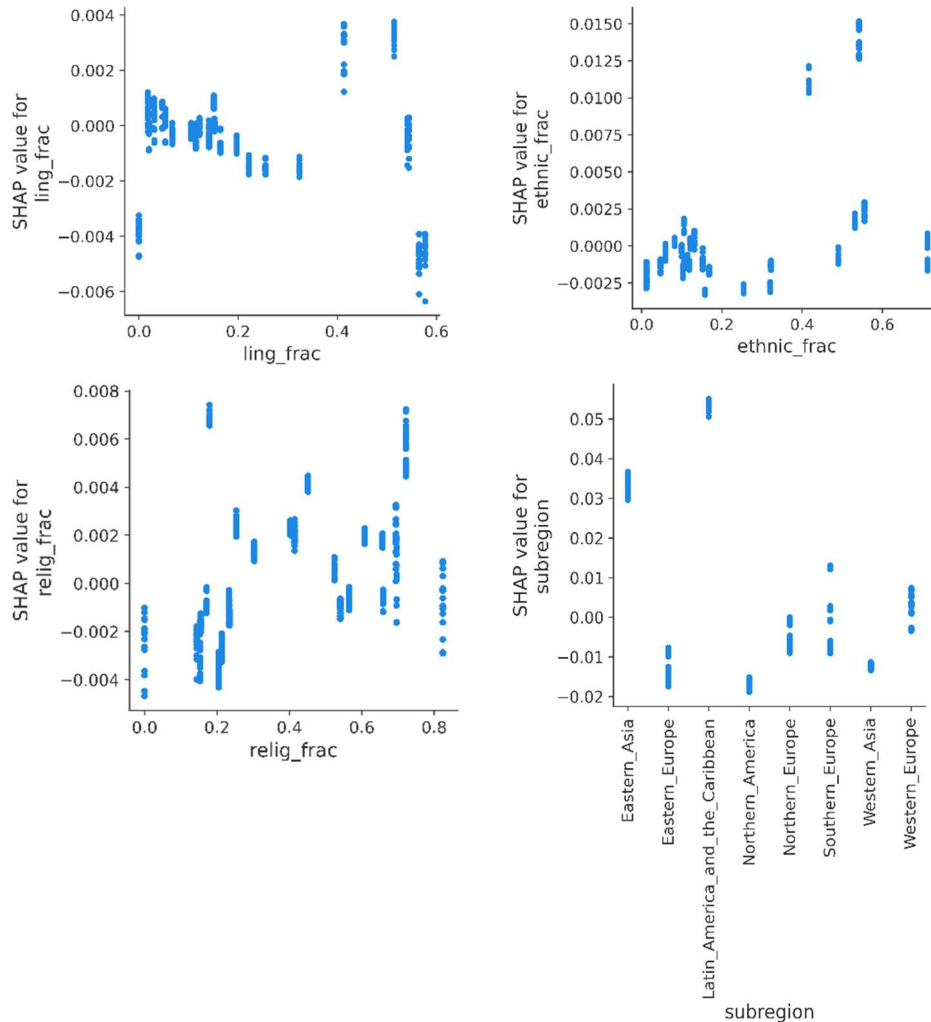
to its poor balancing, while it shows that subregions are strongly homogeneous with respect to the target variable.

Figure 7. SHAP Partial Dependence Plots based on CatBoost model
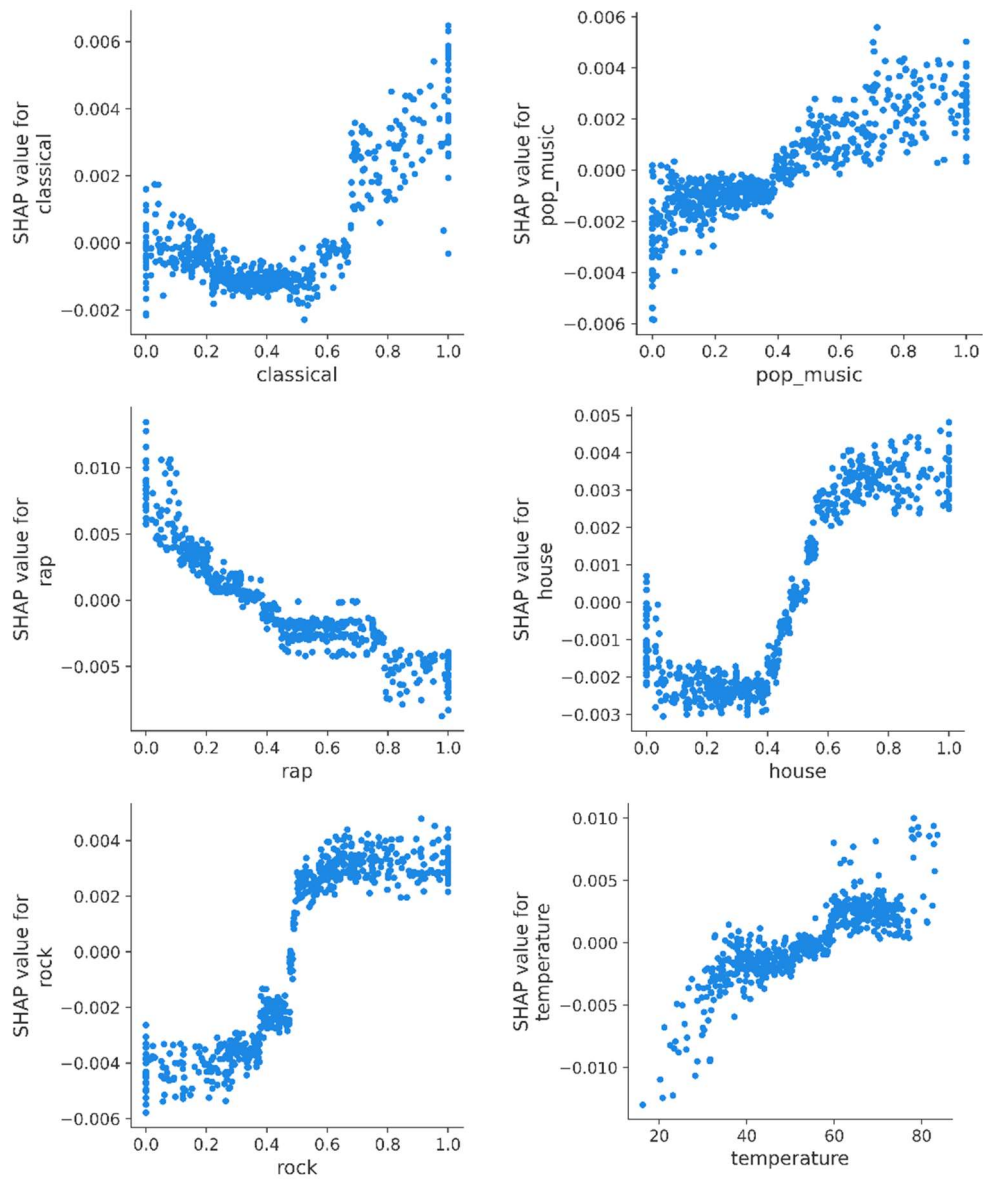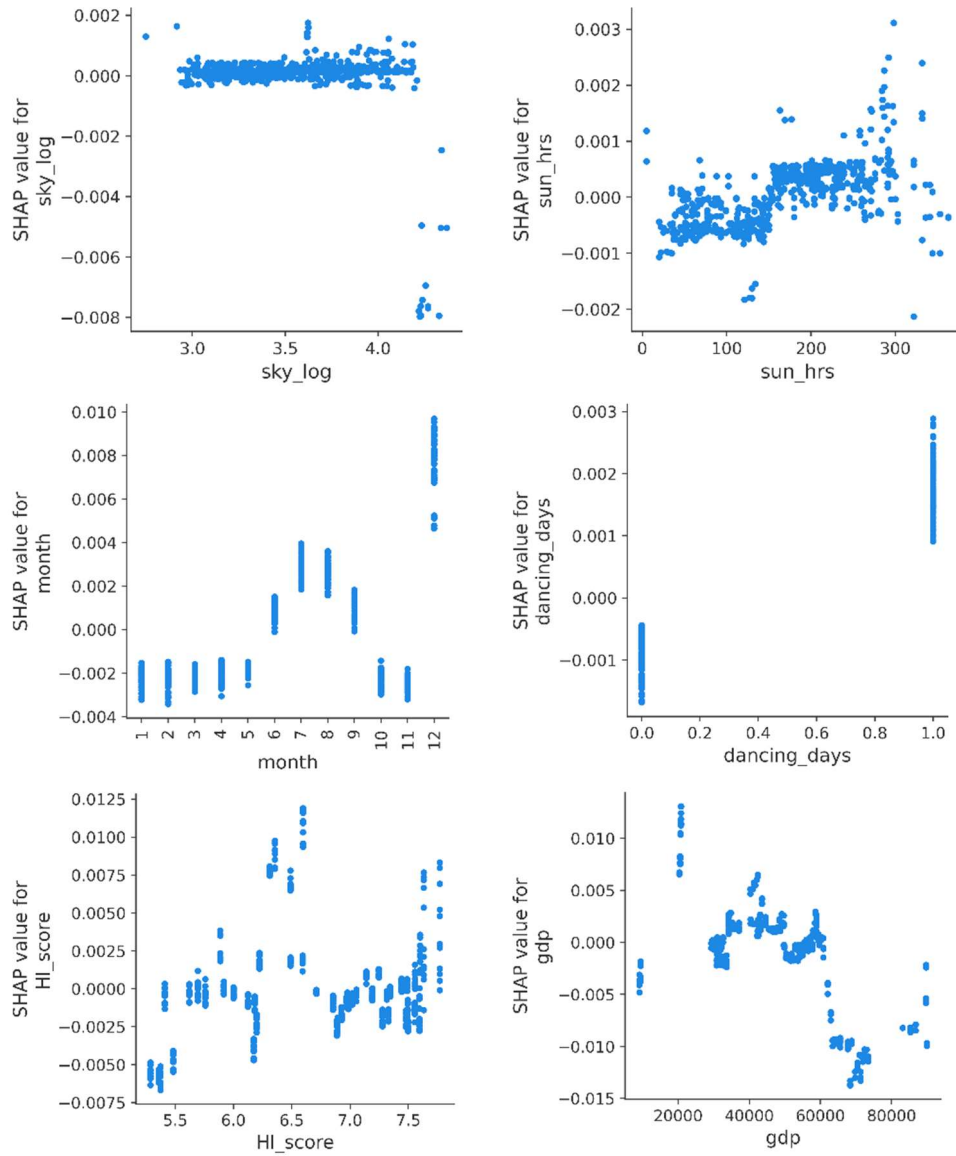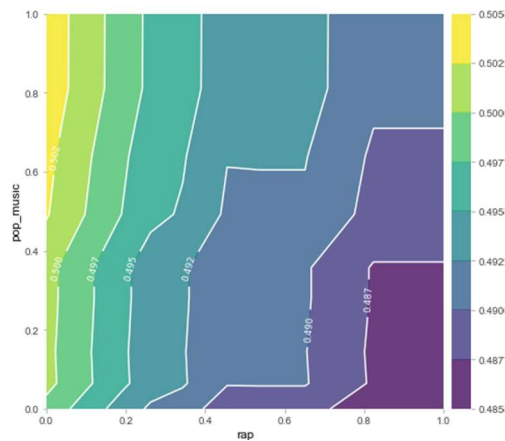
Source: own calculations

According to the SHAP Partial Dependence Plots analysis for music genres, it has been observed that the impact of classical music is negligible for low popularity and declines further to negative levels, but increases rapidly from the point of 0.6. In the case of pop music, the relationship is linear with a slightly negative start and ending at a level slightly lower than the maximum level for classical music. On the other hand, for rap music, the relationship is negative with a significantly positive start, but it declines linearly to reach similar values as pop and classical music in the negative direction. The impact of house and rock music is similar to classical music but with sharper changes. The temperature has a positive linear relationship, starting from the negative end and increasing towards the

positive. The logarithmical cloudiness of the sky and sun hours do not have any significant impact. Five months, namely June, July, August, September, and December, have a positive impact, whereas the absence of dancing days has a negative impact.

Variables such as HI_score, v2xc_prpty, v2claclfree, v2clrelig, v2x_corr, ling_frac, ethnic_frac, and relig_frac seem to have no significant effect, and their probable effect is around zero. The effect of GDP is similar, but from a certain point, it has a negative impact. The impact of v2x_rule is slightly negative, but it increases sharply to much more positive values for values close to 1.0. On the other hand, the effect is reversed for v2xcl_disc, starting at high but ending slightly below zero. Some regions such as Eastern Asia, Latin America, and the Caribbean have a more positive impact, whereas Eastern Europe, Northern America, and Western Asia have a negative impact. Other regions show a neutral impact.

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
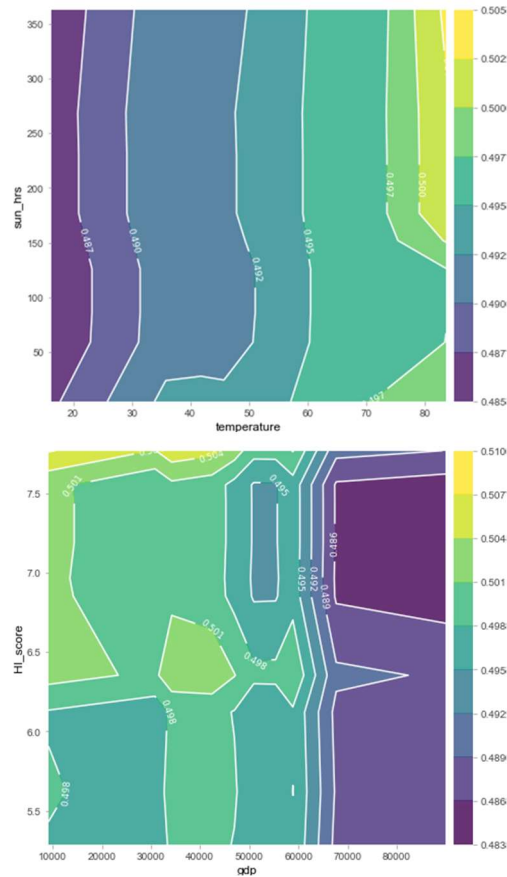
Source: own calculations

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.

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 models confirmed both the importance of macroeconomic and environmental variables. However, the results for the first ones were not clear. For GDP we found both a negative relationship and a positive one, the happiness index sometimes turned out to be irrelevant, and for other macroeconomic variables, the SHAP graphs (machine learning model) indicated a non-linear relationship. For environmental variables, the relationships turned out to be linear and consistent between the models. This indicates the need for further analysis of musical preferences with macro variables and the inability to distinguish one category of variables that would prevail, so the phenomenon should be analyzed in the context of both of these phenomena. 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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