Warsaw University of Life Sciences – SGGW
Institute of Economics and Finance
Department of Econometrics and Statistics

QUANTITATIVE METHODS IN ECONOMICS

METODY ILOŚCIOWE W BADANIACH EKONOMICZNYCH

Volume XXIV, No. 1

Warsaw 2023

ISSN 2082-792X
e-ISSN 2543-8565

Warsaw 2023, Volume XXIV, No. 1
Journal homepage: https://qme.sggw.edu.pl
Published by Warsaw University of Life Sciences Press

QUANTITATIVE METHODS IN ECONOMICS
Volume XXIV, No. 1, 2023

CONTENTS

QUANTITATIVE METHODS IN ECONOMICS
Volume XXIV, No. 1, 2023, pp. 1 – 26

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

https://doi.org/10.22630/MIBE.2023.24.1.1

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. 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

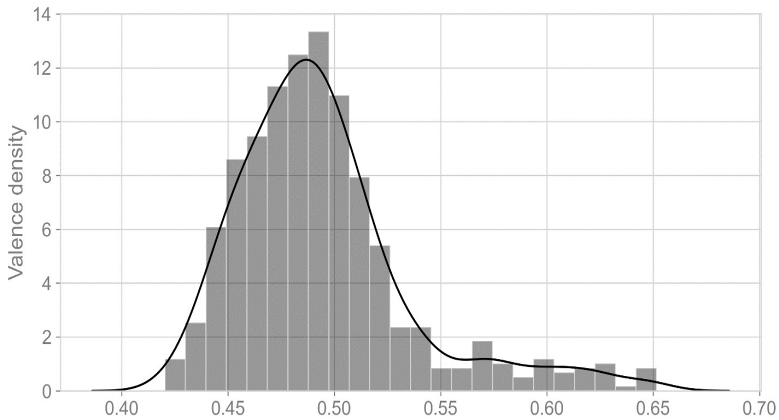
Source: own calculations

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.

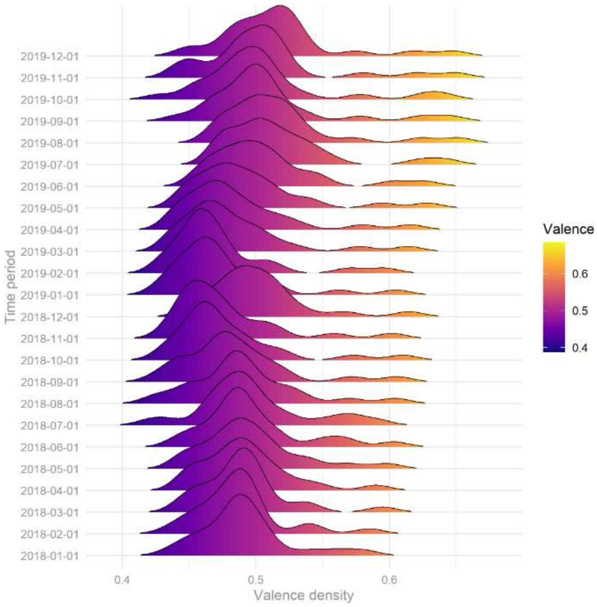
Figure 1. Kernel Density Estimate (KDE) plot with histogram for Valence



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.

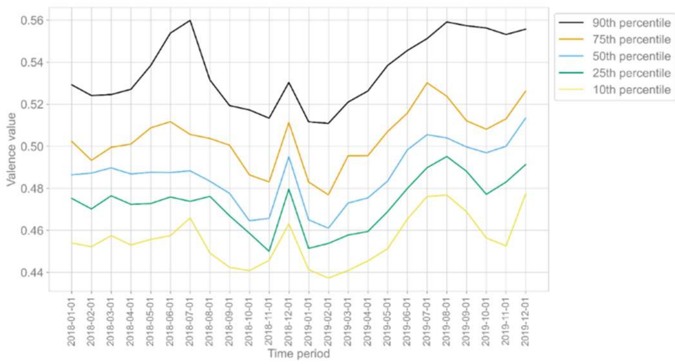
Figure 2. Valence probability density over the time segregated from the most recent (at the top) to the oldest (at the bottom)



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.

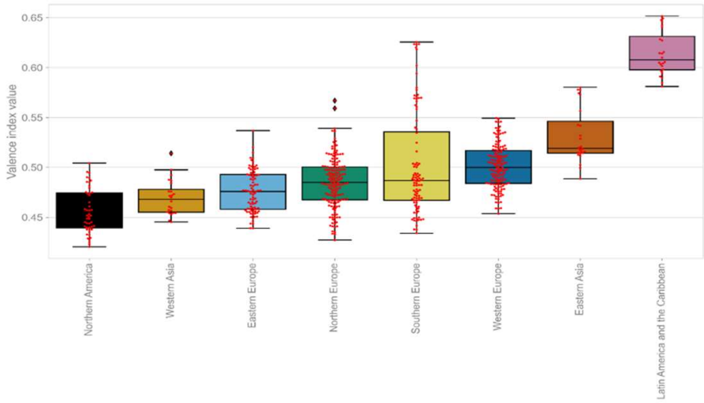
Figure 3. Quantile trend plot for Valence



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.

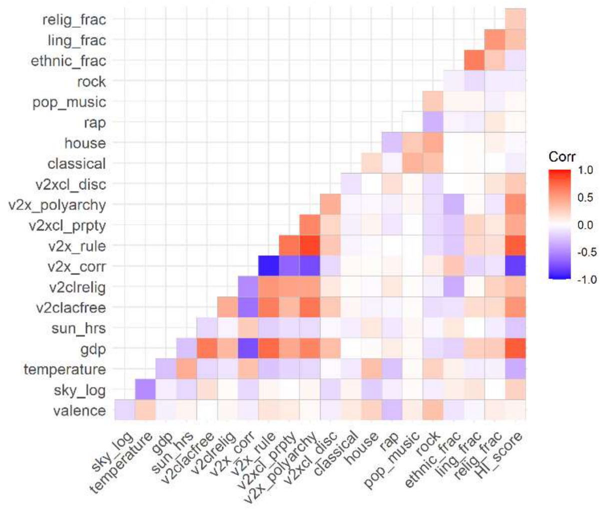
Figure 4. Valence in particular subregions



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

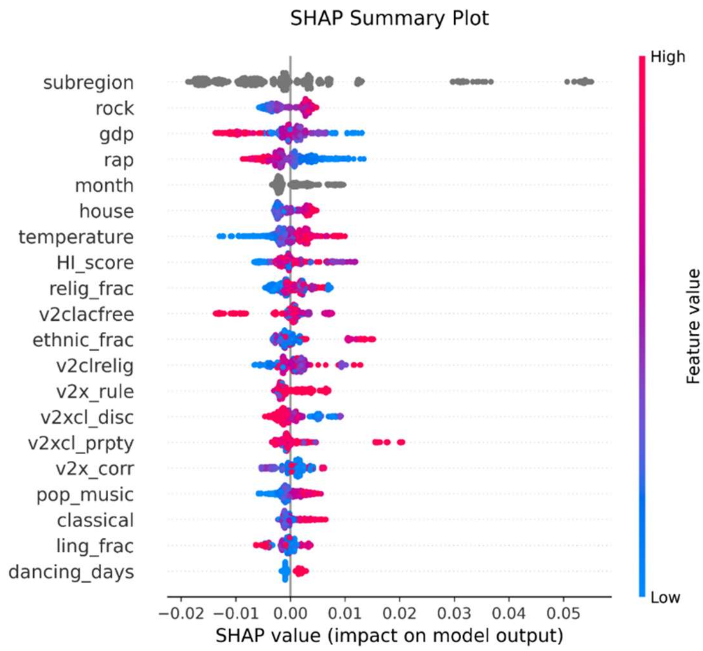
Table 3 presents the results obtained from the Arellano and Bover/Blundell and Bond system estimator on dynamic panel data. The General-to-Specific approach was used to select the final model, and in Table 3, we present the results of the last three iterations of this approach, which include model 1,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

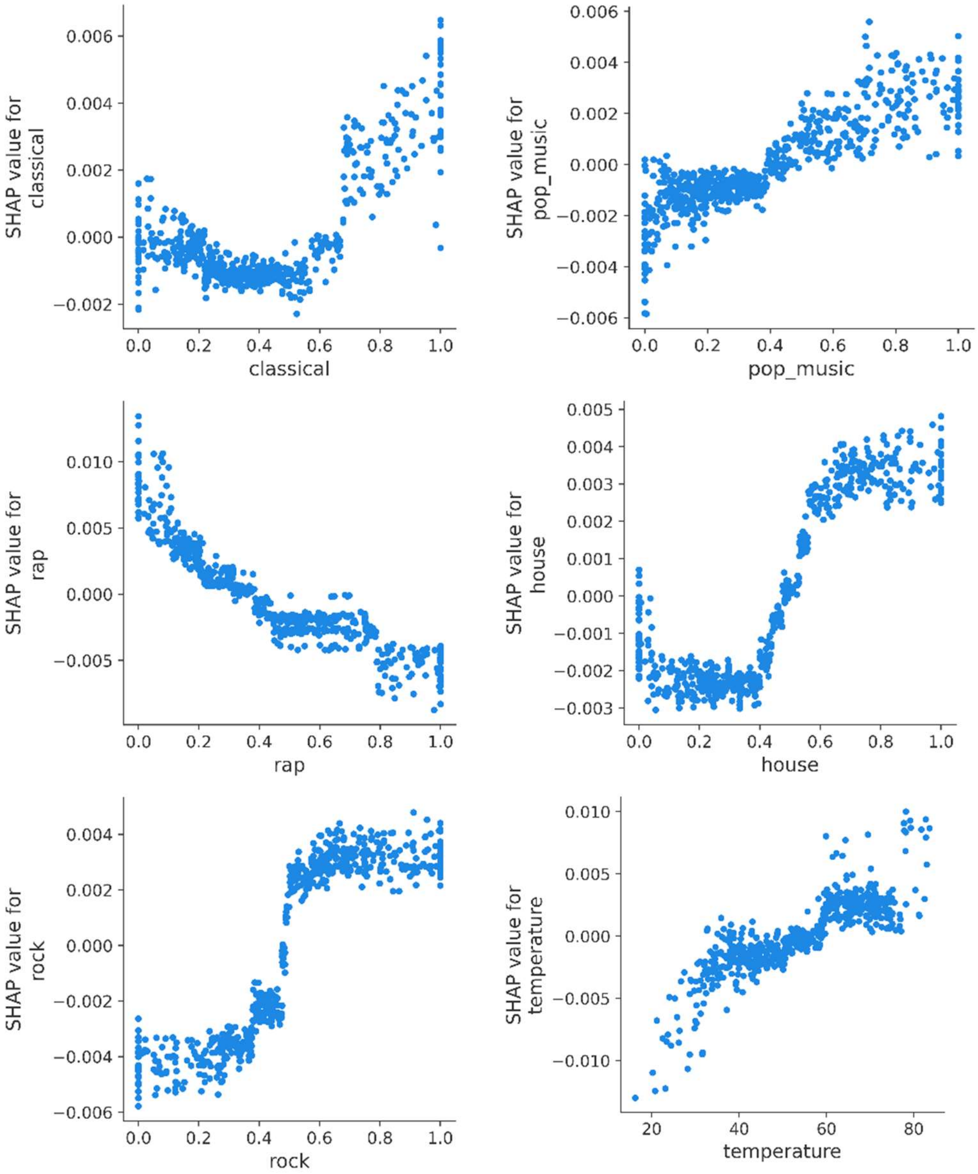
Figure 6. SHAP Summary Plot based on CatBoost model

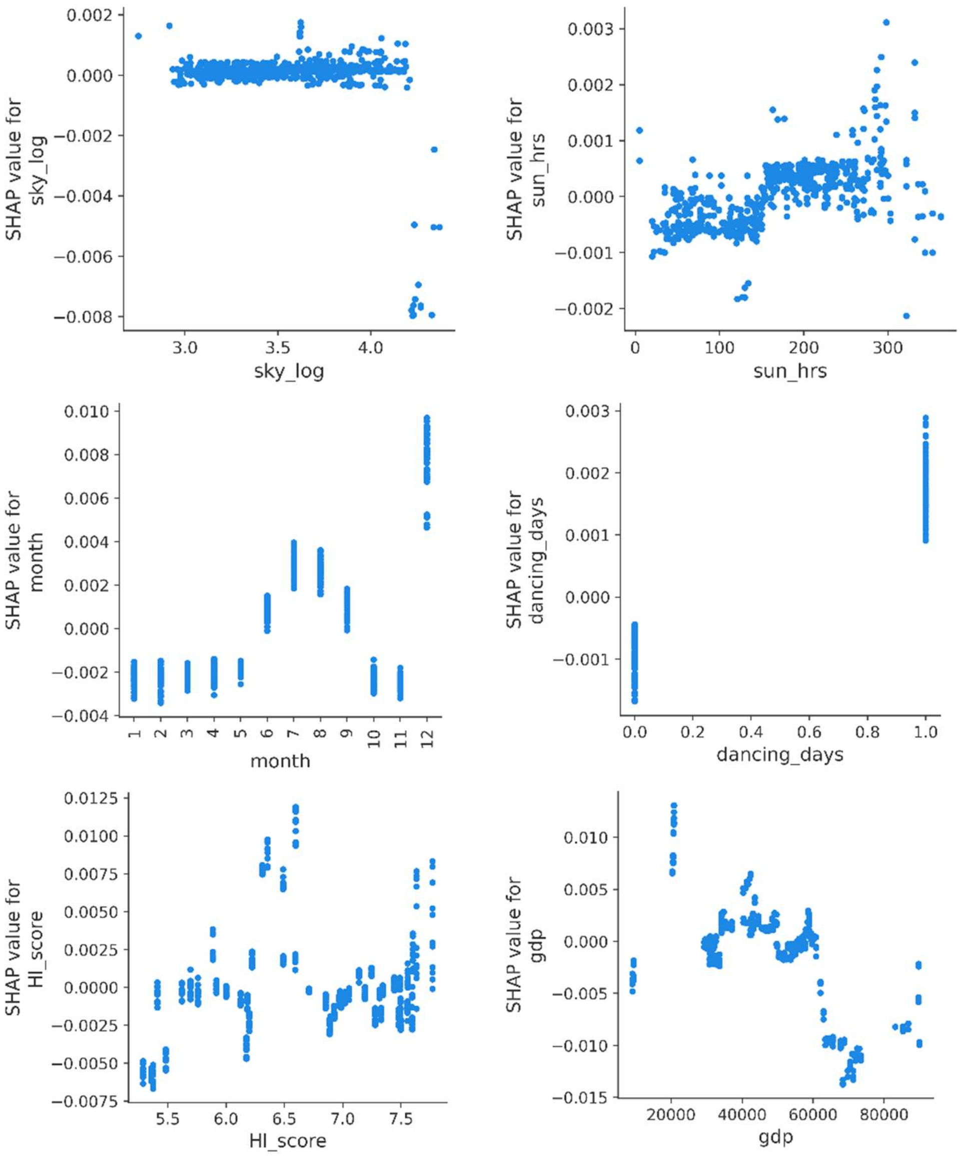


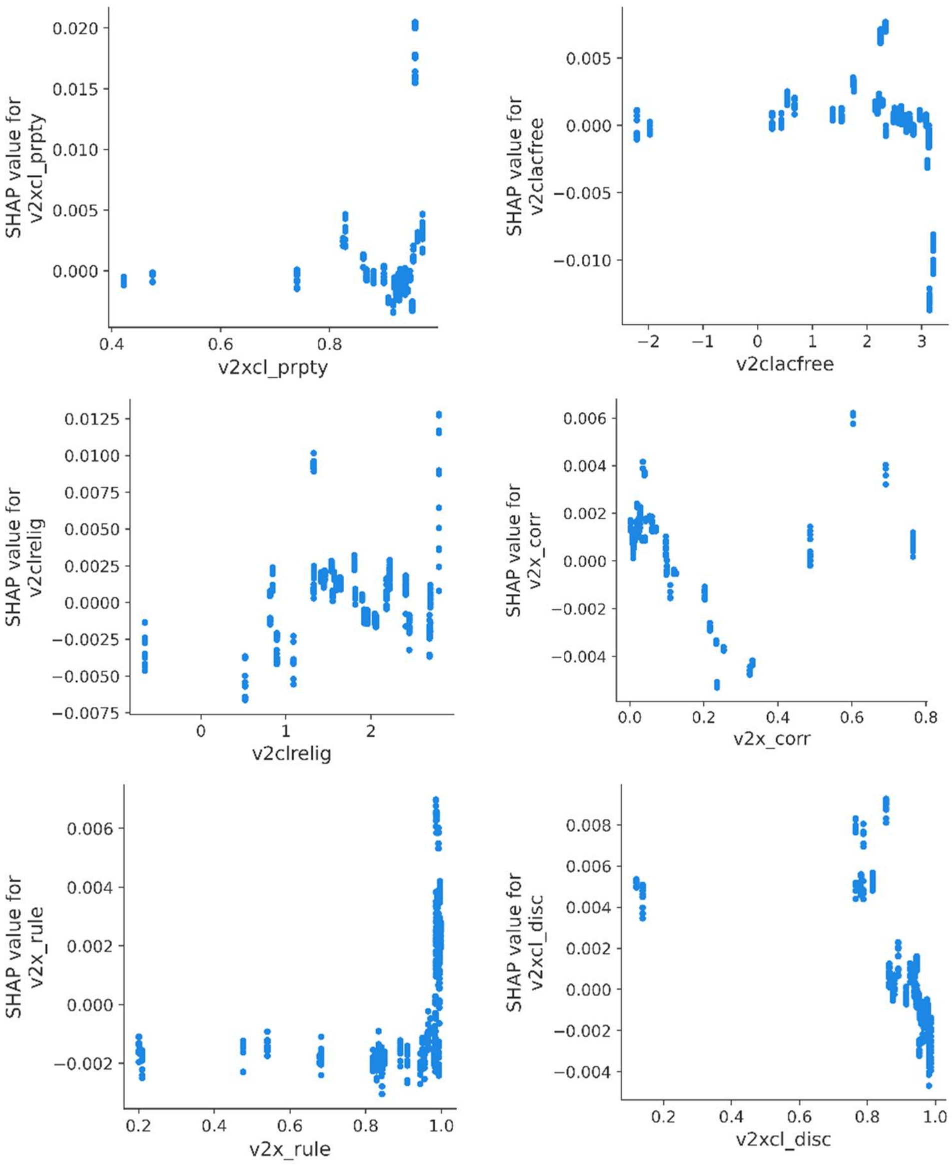
Source: own calculations

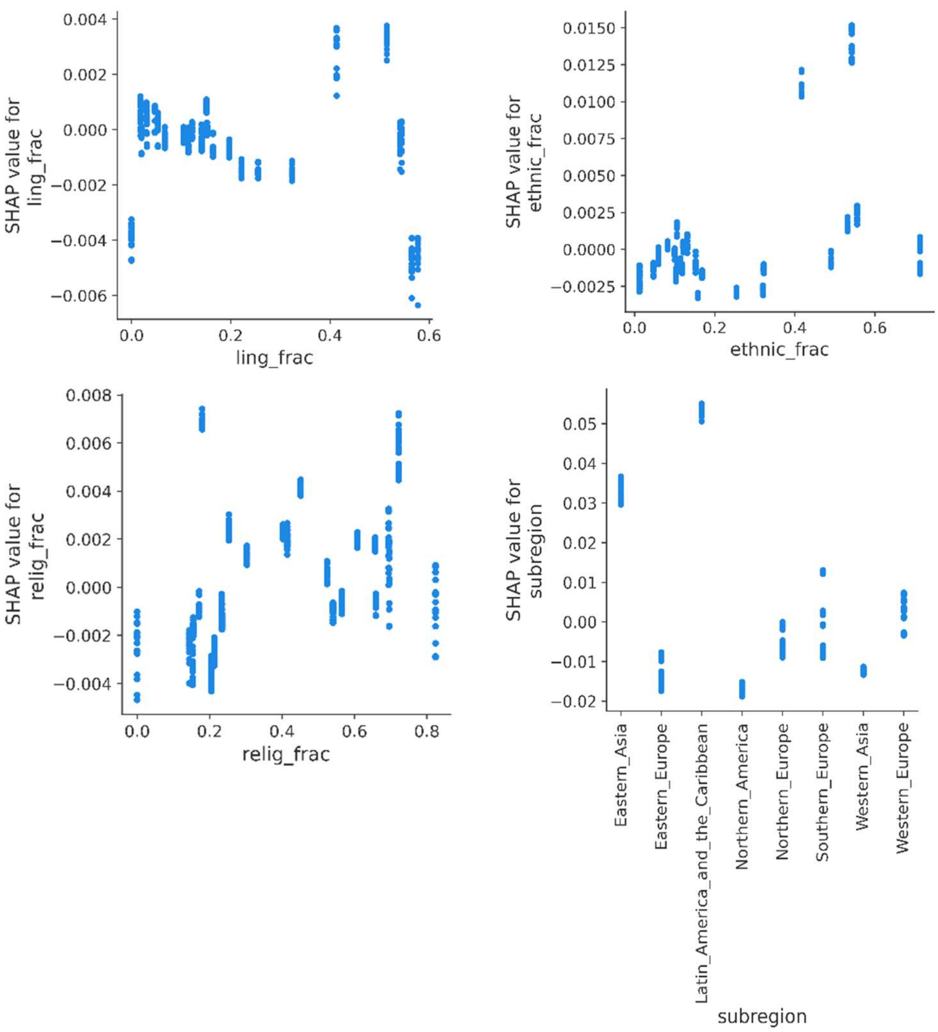
Let us first analyze the influence of music genres. We can easily conclude that the greater popularity of pop, house, rock in each country, the greater the valence. The effect of rap is strictly negative, while the popularity of classical music only has a measurable positive effect on the expected value 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




SHAP value for sky_log
sky_log
SHAP value for sun_hrs
sun_hrs
SHAP value for month
month
SHAP value for dancing_days
dancing_days
SHAP value for HI_score
HI_score
SHAP value for gdp
gdp


SHAP value for v2xcl_prpty
v2xcl_prpty
SHAP value for v2clacfree
v2clacfree
SHAP value for v2clrelig
v2clrelig
SHAP value for v2x_corr
v2x_corr
SHAP value for v2x_rule
v2x_rule
SHAP value for v2xcl_disc
v2xcl_disc



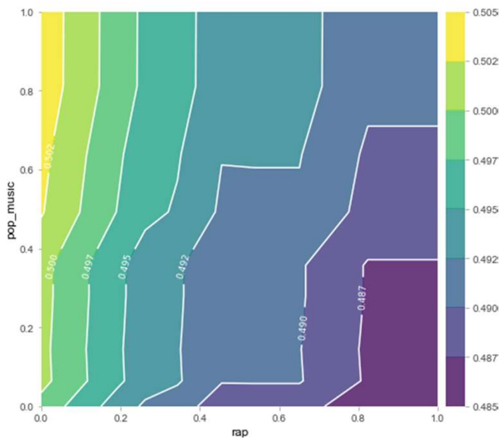
Source: own calculations

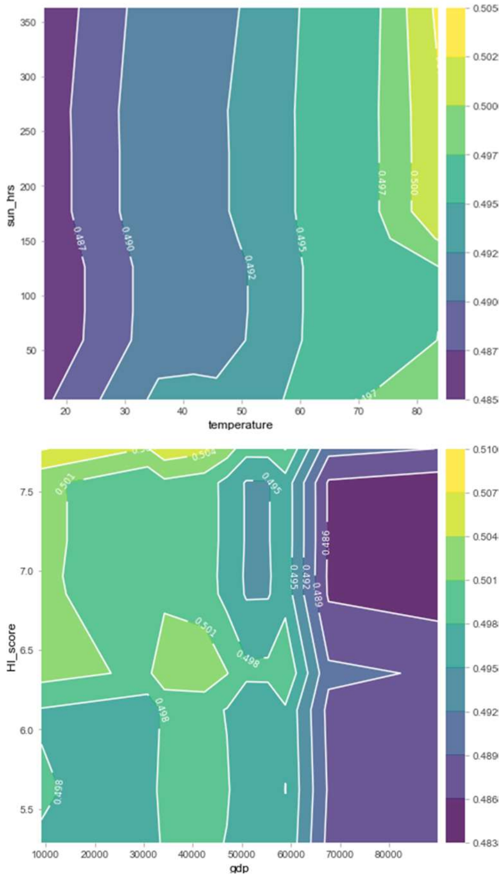
According to the SHAP Partial Dependence Plots analysis for music genres, it has been observed that the impact of classical music is negligible for low popularity and declines further to negative levels, but increases rapidly from the point of 0.6. In the case of pop music, the relationship is linear 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.

REFERENCES

Alesina A., Devleeschauwer A., Easterly W., Kurlat S., Wacziarg, R. (2003) Fractionalization. Journal of Economic Growth, 8(2), 155-194. https://doi.org/10.1023/A:1024471506938

Baltrunas L., Amatriain X. (2009) Towards Time-Dependent Recommendation Based on Implicit Feedback. [In:] Workshop on Context-Aware Recommender Systems, 25-30.

Campos J., Ericsson N. R., Hendry D. F. (2005) General-to-Specific Modeling: an Overview and Selected Bibliography. FRB International Finance Discussion Paper, 838.

Coppedge M., Gerring J., Knutsen C. H., Lindberg S. I., Teorell J., Altman D., Ziblatt D. et al. (2020) V-dem Dataset v10. Varieties of Democracy (V-Dem) Project. https://doi.org/10.23696/vdemds20

Herrera P., Resa Z., Sordo M. (2010) Rocking around the Clock Eight Days a Week: an Exploration of Temporal Patterns of Music Listening. In 1st Workshop On Music Recommendation and Discovery, ACM RecSys, 2010, Barcelona, Spain.

Efroymson, M. A. (1960) Multiple Regression Analysis. Mathematical Methods for Digital Computers, 191-203.

Friedman R. S., Gordis E., Förster J. (2012) Re-Exploring the Influence of Sad Mood on Music Preference. Media Psychology, 15(3), 249-266. https://doi.org/10.1080/15213269.2012.693812

Hospers J. (1969) Introductory Readings in Aesthetics. Free Press.

Kellaris J. J. (2008) Music and Consumers in Haugtvedt, C. P., Herr, P. M., & Kardes, F. R. (Eds.) (2018) Handbook of Consumer Psychology, 837-856. Routledge.

Kim J.-H., Jung K.-Y., Ryu J.-K., Kang U.-G., Lee J.-H. (2008) Design of Ubiquitous Music Recommendation System using MHMM. Int. Conf. on Networked Computing and Advanced Information Management, 2, 369-374.

Lai H. L. (2004) Music Preference and Relaxation in Taiwanese Elderly People. Geriatric Nursing, 25(5), 286-291. https://doi.org/10.1016/j.gerinurse.2004.08.009

Lee J. S., Lee J. C. (2007) Context Awareness by Case-based Reasoning in a Music Recommendation System. In International Symposium on Ubiquitious Computing Systems, 45-58. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-76772-5_4

Levinson J. (1997) Music and Negative Emotion. [In:] J. Robinson (Ed.) Music and Meaning (215-241) Ithaca, NY: Cornell University Press.

Liu M., Hu X., Schedl M. (2018) The Relation of Culture, Socio-Economics, and Friendship to Music Preferences: A large-Scale, Cross-Country Study. PloS one, 13(12).

Lundberg S.M., Lee S. (2017) A Unified Approach to Interpreting Model Predictions, Advances in Neural Information Processing Systems, 30, 4765-4774.

McFerran K. S., Garrido S., O'Grady L., Grocke D., Sawyer S. M. (2015) Examining the Relationship between Self-Reported Mood Management and Music Preferences of Australian Teenagers. Nordic Journal of Music Therapy, 24(3), 187-203. https://doi.org/10.1080/08098131.2014.908942

McFerran K. S. (2016) Contextualising the Relationship between Music, Emotions and the Well-Being of Young People: A Critical Interpretive Synthesis. Musicae Scientiae, 20(1), 103-121. https://doi.org/10.1177/1029864915626968

Mellander C., Florida R., Rentfrow P. J., Potter J. (2018) The Geography of Music Preferences. Journal of Cultural Economics, 42(4), 593-618. https://doi.org/10.1007/s10824-018-9320-x

Pettijohn T. F., II, Sacco D. F., Jr. (2009) Tough Times, Meaningful Music, Mature Performers: Popular Billboard Songs and Performer Preferences across Social and Economic Conditions in the USA. Psychology of Music, 37, 155-179. https://doi.org/10.1177/0305735608094512

Prokhorenkova L., Gusev G., Vorobev A., Dorogush A. V., Gulin A. (2017) CatBoost: Unbiased Boosting with Categorical Features. arXiv preprint arXiv:1706.09516.

Rentfrow P., Mellandar C., Florida R., Hracs B. J., Potter J. (2013) The Geography of Music Preferences.

Rentfrow P. J., Gosling S. D. (2003) The Do Re Mi's of Everyday Life: the Structure and Personality Correlates of Music Preference. Journal of Personality and Social Psychology, 84, 1236-1253. https://doi.org/10.1037/0022-3514.84.6.1236

Roe K. (1987) The School and Music in Adolescent Socialisation. In J. Lull (Ed.), Pop Music and Communication, 212–230. Thousand Oaks, CA: Sage.

Skowron M., Lemmerich F., Ferwerda B., Schedl M. (2017) Predicting Genre Preferences from Cultural and Socio-Economic Factors for Music Retrieval. Advances in Information Retrieval, 561-567. Springer, Cham. https://doi.org/10.1007/978-3-319-56608-5_49

Schedl M., Lemmerich F., Ferwerda B., Skowron M., Knees P. (2017) Indicators of Country Similarity in Terms of Music Taste, Cultural, and Socio-Economic Factors. In 2017 IEEE International Symposium on Multimedia (ISM), 308-311. https://doi.org/10.1109/ISM.2017.55

Scherer K. R. (2004) Which Emotions Can Be Induced by Music? What Are the Underlying Mechanisms? And How Can We Measure Them?. Journal of New Music Research, 33(3), 239-251. https://doi.org/10.1080/0929821042000317822

The Economist (2020) Data from Spotify Suggest that Listeners are Gloomiest in February. The Economist. https://www.economist.com/graphic-detail/2020/02/08/data-from-spotify-suggest-that-listeners-are-gloomiest-in-february

Took K. J., Weiss, D. S. (1994) The Relationship between Heavy Metal and Rap Music on Adolescent Turmoil: Real or Artifact? Adolescence, 29, 613-621.

Vigliensoni G., Fujinaga I. (2016) Automatic Music Recommendation Systems: Do Demographic, Profiling, and Contextual Features Improve Their Performance?. Proceedings of the 17th ISMIR Conference, New York City, USA, 94-100.

Vlegels J., Lievens J. (2017) Music Classification, Genres, and Taste Patterns: A Ground-up Network Analysis on the Clustering of Artist Preferences. Poetics, 60, 76-89. https://doi.org/10.1016/j.poetic.2016.08.004

Vuoskoski J. K., Thompson W. F., McIlwain D., Eerola T. (2011) Who Enjoys Listening to Sad Music and Why?. Music Perception, 29(3), 311-317. https://doi.org/10.1525/mp.2012.29.3.311

QUANTITATIVE METHODS IN ECONOMICS
Volume XXIV, No. 1, 2023, pp. 27 – 46

THE LEVEL OF SOCIO-ECONOMIC DEVELOPMENT OF POLISH PROVINCES IN THE PERIOD 2005-2020

Ewa Szczucka https://orcid.org/0000-0002-3764-311X
Michał Gostkowski https://orcid.org/0000-0003-3606-1182
Institute of Economics and Finance
Warsaw University of Life Sciences – SGGW, Poland
e-mail: ewa_szczucka@sggw.edu.pl; michal_gostkowski@sggw.edu.pl

Abstract: Socio-economic development is a multi-dimensional and highly complex subject. The goal of the current regional policies, which are widely implemented around the world, is to equalize the level of development of regions. In order for these measures to be effective, there is a need for developing methods and its continuous improvement. One method that allows statistical and multidimensional description of the level of socio-economic development is the determination of synthetic measures. The purpose of the article is to assess the level of socio-economic development of Polish provinces in 2005–2020 and to identify groups of provinces with similar levels of development. The applied methods made it possible to create rankings of provinces. The results of the study showed a high spatial differentiation of the level of socio-economic development in Poland. The provinces with the highest level of socio-economic development in terms of selected variables were the Mazowieckie, Dolnośląskie, Pomorskie and Małopolskie provinces, and those with the lowest were the Podkarpackie, Warmińsko-Mazurskie and Świętokrzyskie.

Keywords: socio-economic development, multidimensional comparative analysis, synthetic measure of development level, provinces of Poland

JEL classification: B40, C38, C43, R10

INTRODUCTION

Socio-economic development is a complex and multifaceted issue that has long been of interest to economists. Although its level was once viewed only through the prism of economic measures, the modern approach is based on taking into

https://doi.org/10.22630/MIBE.2023.24.1.2

account also the social aspects. Such process of shaping of the perception of socio-economic development can be found in the theory of development economics. In the current phase of socioeconomic development, there are regional differences in all countries around the world. These differences affect both the social and economic spheres, and are a key problem of regional policy practice and theory. The growth of natural variations of specific regions in a country is influenced by market forces. Accordingly, public authorities play an important role in reducing regional differences, and do so by pursuing an active regional policy [Kudełko 2004]. Also, the European Union, of which Poland has been a member since 2004, conducts regional policy, the primary goal of which is to reduce differences in the level of development of less developed areas [Adamiec 2017]. However, in order to carry out activities related to equalizing the level of development of regions, it is first necessary to make appropriate assessment.

The main purpose of the article was to characterize the spatial differentiation of the level of socio-economic development of Polish provinces during selected years within the period 2005-2020, and to analyze and compare the results in relation to selected methods (standardized sums method and Hellwig method), as well as to classify the provinces in terms of the level of development. It also formulated the following specific research objectives:

1. To verify whether the Mazowieckie province was ranked as first in all the years analyzed.
2. To evaluate the differences and consistency of the constructed rankings results.
3. To determine the similarities and differences in the classifications based on selected methods.

The article also sought to answer the research questions. The first was: can a decrease in values be observed for any of the selected diagnostic variables? The second was: in classifications based on selected methods, is the same provinces assigned to groups with the lowest level of socio-economic development?

The scientific contribution of the article was the development of two synthetic measures of the level of socio-economic development for provinces in Poland and their calculation for the years 2005, 2010, 2017 and 2020, as well as a comparison of the rankings of provinces and the classifications created. The synthetic measures were constructed on the basis of an existing, but modified and revised set of diagnostic variables. Compared to the results of the study, which used the original set of diagnostic variables for calculations, in this article the time frame was extended to include the year 2020. The data underlying the study came from the databases of the Statistics Poland – Local Data Bank. Methods of multivariate comparative analysis, i.e., the method of standardized sums and the method of Hellwig's development pattern, as well as the method of grouping objects into classes using a rule based on standard deviation and mean and Spearman's rank correlation, were used to assess the differentiation of the level of development.

The chapter including the literature review discusses the concept of socioeconomic development and its current perception related to the development economics theory. Next, the data used for the analyses was characterized, including the names of categories, groups and subgroups in the database of the Local Data Bank of the Central Statistical Office. The methodological chapter discusses the methods used, cites the formulas used in the analyses and presents the research procedure. The next part of the article is devoted to the results of the empirical research and is divided into four subsections. The first characterizes the synthetic measure of the level of development used in the study, the second presents the rankings of provinces in terms of the level of socio-economic development they have achieved, the third presents the classification of provinces taking into account the four groups relating to the level of development, and the fourth contains a discussion.

SOCIO-ECONOMIC DEVELOPMENT AND DEVELOPMENT ECONOMICS THEORY

Economic or socioeconomic development, as well as theories on the causes of its variation, have long been the subject of scholarly work in economics and socioeconomic geography [Churski 2012, p. 14]. It can be considered that one of the theories underlying the flourishing of research on socioeconomic development is the theory of development economics. The origins of this concept date back to the early 1940s [Bartkowiak 2010]. The concept of development economics itself originated from the desire to support the economic development of newly emerging post-colonial states. Initially, the development of countries was considered in the context of changes in the level of gross domestic product, and the development of a region was closely identified with economic development. At that time, such theoretical considerations of development economics as P. Rosenstein-Rodan's [1943] "big push" theory, R. Nurkse's [1953] sustainable growth theory, V. Rostow's [1956] "take-off" theory for self-growth, or H. Leibenstein's [1957] "minimum critical effort" theory were dominant.

Over time, in the 1970s, such an approach was modified and social determinants also began to be taken into account in considering development economics. The breakthrough event turned out to be the publication in 1969 of a study entitled "The World Employment Program" [Thorbecke 2006]. After that, the well-being of the individual became as important as economic development, and there was a definition of the basic needs of the individual, among which was access to health-related infrastructure [Johnston, Kilby 1975]. Nowadays, it is recognized that the potential for providing well-being to society is as important an aspect in assessing the level of development of regions as economic factors. This is confirmed by a large number of studies that include social aspects in the evaluation of a region, as well as global indicators assessing the socio-economic level that incorporate non-economic factors. An example is the Human Development Index (HDI), also called the Socio-Economic Development Index, which is based on measures that include health and education indicators in addition to economic factors [Human Development… 2022].

Socio-economic development is a very broad concept and, according to D. Strahl [1998], takes into account the impact of three areas. The first is the economy-wide phenomena that shape the level of countries' economies and thus affect the living conditions of residents. The next area includes the residential environment, i.e. the housing situation, the labor market and public safety. The last area consists of institutions providing social services related to education, culture, upbringing, social welfare or health care.

In the classic typology of regions by L. Klaassen [1965, as cited in: Kudełko 2004], due to the pace and level of development, four fundamental types are distinguished. These are regions:

- highly developed and rapidly developing,
- highly developed but developing more slowly,
- underdeveloped but developing relatively fast,
- underdeveloped and slow developing.

Since the socioeconomic level is a multi-faceted and complex phenomenon, it is not possible to calculate it using a single indicator. One method that allows a statistical and multidimensional description of it is to determine a synthetic measure of level development. In developing synthetic measures, a number of often subjective decisions must be made regarding, among other things, the type of measure (benchmark or model-free methods), the choice of diagnostic variables, the method of normalization or the criteria for classifying objects. Despite this, using them, it is possible to concretize a fairly thorough and objective description of objects, as well as to organize and classify them [Malina 2020, p. 143].

Synthetic measures of development are considered the basic tool of analytical multidimensional comparative analysis derived from taxonomic methods. The purpose of the methods using it is to organize a set of objects of any specificity, which are included in a multidimensional classification space determined by a set of properties describing the elements under study [Grabiński et al. 1982]. Synthetic measures of the level of socio-economic development are widely used both at the regional [Bartkowiak-Bakun 2015; Dziekański 2014; Kutkowska et al. 2015; Roman 2018], national [Kudełko 2004; Malina 2004; Malina 2020] and global [Stec 2004] levels. In the literature regarding multivariate comparative analysis, a number of procedures have been developed, which differ, among other things, in methods when normalizing variables, determining variable weights or estimating the value of synthetic variables [Bąk 2018].

DATA

The data used in the research covered four years from the period 2005-2020 and were obtained from secondary sources, i.e. the database of the Local Data Bank (LDB) of the Central Statistical Office (GUS). Local Data Bank is the country's largest database of social, economic and environmental data. Data was downloaded for 16 provinces. The data used for the analysis was complete and available for all the years studied during the period under analysis. The names and numbers of categories, groups and subgroups of information locations in the LDB are shown in Table 1.

Table 1. Names and numbers of groups, categories and subgroups in the Local Data Bank for the data used

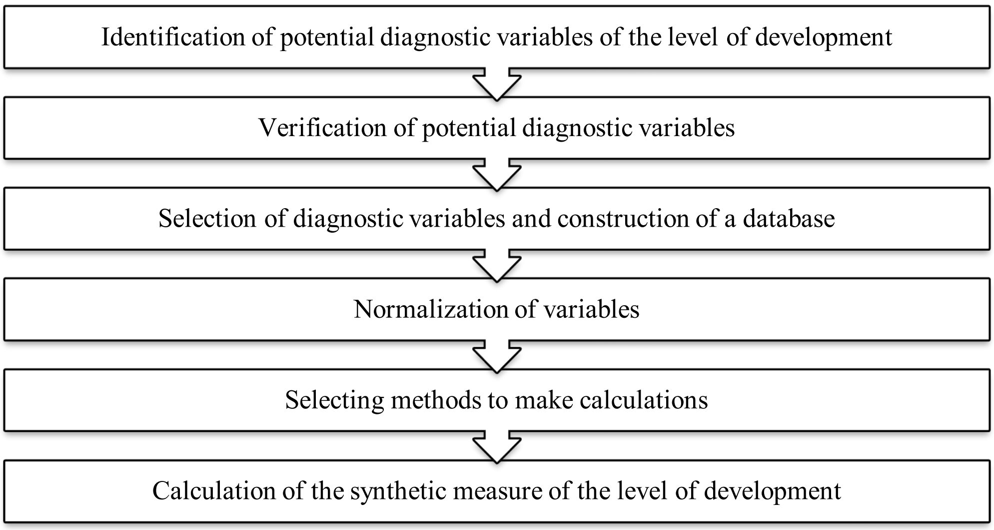
Category		Group		Subgroup	
Name	ID	Name	ID	Name	ID
Wages and salaries and social security benefits	K40	Wages and salaries	G403	Average monthly gross wages and salaries	P2497
Labour market	K4	Registered unemployment	G12	Registered unemployment rate	P2392
Health care, social welfare and benefits to the family	K22	Medical personnel	G265	Doctors – indicators	P3173
Higher education	K21	Indicators	G391	Higher education institutions students per 10 thousand population	P2383
Culture	K23	Performances and exhibitions	G229	Indicators of performances and exhibitions	P2382
Transport and communication	K8	Vehicles	G239	Road vehicles and tractors – indicators	P2420
Tourism	K18	Tourist accommodation establishments and their occupancy	G240	Tourist accommodation establishments – indicators	P2396
Entities of the national economy, ownership and structural transformations	K25	Entities of the national economy – indicators	G377	Entities – indicators	P2419

Source: own preparation based on GUS Local Data Bank

METHODS

The sample selection was purposive and included all provinces in Poland. To assess the socio-economic development of the provinces, an existing synthetic measure was used, which was modified for the purpose of the analyses. The procedure for constructing and calculating synthetic measures of the level of development can be divided into several main stages, which are shown in Figure 1.

Figure 1. Research procedure for constructing a synthetic measure of development level



Source: own preparation

Two methods were chosen for the calculation, i.e. the standardized sum method and the Hellwig development pattern method. Both belong to linear ordering methods, which in turn fall into the category of Multiple-criteria decision analysis (MCDA) methods, also known as Multiple-criteria decision making (MCDM) [Chojnicki, Czyż 1991; Bąk 2018; Koszela et al. 2020]. Hellwig's method was the first proposed linear ordering method in taxonomic and economic research [Hellwig 1968], and in practice is the most frequently chosen method [Wawrzyniak 2015]. In the literature, the comparison of Hellwig's development pattern method and the standardized sum method can be found [Wawrzyniak 2015]. Thanks to methods, it is possible to rank the studied objects in order from the best to the worst in terms of the analyzed phenomenon [Jajuga 1992, pp. 256-261], whereby the characteristics of the objects can be derived from numerous characteristics and properties called diagnostic variables, on the basis of which the so-called synthetic variable is formed [Kisielińska et al. 2021]. Variables that are intended to be arranged should be assessed using an interval scale. In the case where they are assessed using a range or quotient scale, it becomes necessary to normalize them [Gostkowski et al. 2019].

Standardization

The first stage of the process of constructing development measures is the same and consists in standardizing the diagnostic variables, that is, bringing them to comparability by eliminating different ranges of variability and units of measurement. Standardization proceeds according to the formula:

$$z_{ij} = \frac{x_{ij} - \overline{x}_j}{s_j}, \tag{1}$$

where:

- z_{ij} – standardized value of the j-th variable for the i-th object,
- x_{ij} – the value of the j-th variable for the i-th object,
- $\overline{x}_j$ – arithmetic mean of the variable x_j,
- s_j – standard deviation of the variable x_j.

Standardized sum method

The development pattern calculated by the method of standardized sums can be determined after standardizing the variables according to formula (1). It is also necessary to convert the destimulants into stimulants by multiplying their standardized value by -1. After this procedure, the weight matrix is determined, according to the assumption:

$$w_j > 0 \text{ and } \Sigma_j^m w_j = 1. \tag{2}$$

The study established equal weights for all variables. The next step is to determine p_i using the following formula:

$$p_i = \sum_{y=1}^{m} w_j z_{ij}. \tag{3}$$

The resulting ranking reflects the value of the objects. The highest score is obtained by the best object in terms of the selected set of diagnostic variables, and the lowest score characterizes the worst object in the set. In order to transform the results so that they take values in the interval (0,1), the pattern (p_0) and anti-pattern (p_{-0}) should be calculated, using the following formulas:

$$p_0 = \sum_{j=1}^{m} z_{o_j} w_j, \tag{4}$$

$$p_{-0} = \sum_{j=1}^{m} z_{-o_j} w_j, \tag{5}$$

where:

$$z_{0j} = \max_i z_{ij} \text{ and } z_{-0j} = \min_i z_{ij}. \tag{6}$$

The last step is to calculate the final synthetic measure for each object according to the formula:

$$m_i = \frac{p_i - p_{-0}}{p_0 - p_{-0}}. \tag{7}$$

A higher value of the synthetic variable m_i means that the i-th object is more developed from the point of view of the variables considered in the analysis.

Hellwig's development pattern method

After standardizing the diagnostic variables according to formula (1), the development pattern P_0 is determined, whose coordinates $[z_{01}, z_{02}, \ldots, z_{0m}]$ are calculated according to the following procedure:

$$z_{0j} = \begin{cases} \max_i(z_{ij}), \text{when } j \in S, \\ \min_i (z_{ij}), \text{when } j \in D, \end{cases} \quad j = 1, 2, \ldots, m; i = 1, 2, \ldots, n, \tag{8}$$

where:

S – a set of stimulants, i.e. statistical characteristics whose increase in value indicates an increase in the level of a complex phenomenon.

D – a set of stimulants, i.e. statistical characteristics whose decrease in value indicates a decrease in the level of a complex phenomenon.

The next step is to calculate the distance of each object from the pattern determined as described above using the Euclidean distance which has the form:

$$d_{i0} = \sqrt{\sum_{j=1}^{m} \left(z_{ij} - z_{0j}\right)^2}, \quad j = 1, 2, \ldots, m; i = 1, 2, \ldots, n. \tag{9}$$

Finally, the synthetic measure is defined as follows:

$$d_i = 1 - \frac{d_{i0}}{d_0}, \quad i = 1, 2, \ldots, n, \tag{10}$$

where: :

$$d_0 = \bar{d}_0 + 2S_0, \tag{11}$$

$$\bar{d}_0 = \frac{1}{n}\sum_{i=1}^{n} d_{i0}, \tag{12}$$

$$S_0 = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(d_{i0} - \bar{d}_0\right)^2}. \tag{13}$$

Constructed in this way, the measure takes values in the interval (0,1) and the closer its value is to 1, the closer the object is to the benchmark representing the most favorable variable values.

Class designation

Knowing the values of development measures (7) and (10), it is possible to group objects into classes with similar levels of development. One method of grouping is to classify objects into four classes based on a rule based on standard deviation and mean [Malina 2020; Nowak, 1990; Wawrzyniak 2015]. The rule is as follows:

Group I highest level of development): $s_i \geq \bar{s} + sd;$ (14)

Group II (high level of development): $\bar{s} \leq s_i < \bar{s} + sd;$ (15)

Group III (medium level of development): $\bar{s} - sd \leq s_i < \bar{s};$ (16)

Group IV (low level of development): $s_i < \bar{s} - sd,$ (17)

where:

s_i – expression for the value of the synthetic index (in the study, different names were designated for each of the two methods – m_i for the standardized sum method and d_i for the Hellwig development pattern method),

$\bar{s}$ – arithmetic mean of the synthetic indicator,

sd – standard deviation of the synthetic indicator.

RESEARCH RESULTS

The first stage of the research was initially planned to use 29 potential diagnostic variables reflecting eight categories. Due to the lack of data for all years, negligible discriminatory ability and high correlation coefficient in the field, eight variables were left to build a synthetic measure [Malina 2020]. The original intention was to use the same set of variables, but as a result of repeating the calculations for the years 2005, 2010 and 2017, the name of one variable was modified, and a variable from the "culture" category was replaced by another. A coefficient of variation value of greater than or equal to 10% was assumed. Table 2 presents the final summary of the variables representing each field, and gives their name, nature (stimulants or destimulants) and the percentage value of the coefficient of variation for 2020. The basic parameters of the variables for 2005, 2010, 2017 and 2020 are indicated in Appendix 1.

Considering the data in Table 2 and Appendix 1, it can be concluded that the variables chosen to construct the synthetic measure of the level of development exceed the assumed lower limit of the coefficient of variation ($V > 10\%$ for at least one year), and therefore have sufficient discriminatory capacity. In the provinces of Poland, the least variation was seen in the number of passenger cars per 1,000 population (X_6), as well as in the average gross monthly salary per person (X_1).

With six of the eight variables in relation to the average value, favorable changes can be observed in each successive year analyzed, i.e. increasing values for variables that are stimulants and decreasing values for variables that are destimulants. Unfavorable changes can be observed in only two cases. The first is the average number of college students per 10,000 people (X_4), which with each analyzed year presented a lower value than the previous one. The second case can be seen in the number of tourists using overnight accommodation per 1,000 people, where the average value increased until 2017, only to fall in 2020 to a lower level than in 2010. This was likely related to the COVID-19 pandemic and the restrictions put in place at the time.

Table 2. List of diagnostic variables used to calculate the synthetic measure of socio-economic development

Category	Symbol and name of variable	Nature of variable	Coefficient of variation
Population income	X_1 – average monthly gross wages and salary per person [PLN]	stimulant	9.09
Labor market	X_2 – registered unemployment rate [%]	destimulant	25.60
Health care	X_3 – doctors entitled to practise medical profession per 10 thousand population[1]	stimulant	19.93
Education	X_4 – higher education institutions students per 10 thousand population	stimulant	33.14
Culture	X_5 – persons per 1 seat in theatres and musical institutions[2]	destimulant	58.12
Infrastructure and transportation	X_6 – passenger cars per 1000 population	stimulant	6.61
Tourism	X_7 – tourists accommodated per 1000 capita	stimulant	44.62
Economic potential	X_8 – entities entered in the REGON register per 10 thousand population	stimulant	16.93

Source: own compilation based on Malina [2020]

The unfavorable situation was evidenced by positive values of skewness for variables that are stimulants, which meant that the value of the results of more

[1] In the article by A. Malina [2020], the name of the diagnostic variable that was included in the final set of variables referred to doctors working by primary place of work per 10,000 people. It was noted that data for this variable were not available for 2005. Repeating the calculations, based on the average values of the variables for all years, it was found that the variable used referred to doctors with a licence to practice medicine per 10,000 population. The name of the variable has been corrected in the set of variables in this article.

[2] In the article by A. Malina [2020] in the category "culture" the variable referred to the number of population per 1 theatre. A search of the Local Data Bank database did not find such an indicator. Moreover, after analysing the average value for the indicator used by the author, which was approximately 11 for all the years covered by the study, it turned out that there would have to be more than 3.3 million theatres operating in Poland at that time, which is an overestimation – for example, in Poland in 2017 there were 187 theatres and music institutions conducting stage activities [Activities of centres... 2018]. Therefore, the diagnostic variable was changed to an indicator referring to population per 1 seat in theatres and musical institutions.

provinces was lower than the average value. The implication is that few provinces scored high enough to stand out from the rest. The variable X_1 referring to the average gross monthly salary per person and the variable X_5 characterizing the population per 1 seat in theaters and musical institutions were characterized by a high value of the asymmetry measure. With regard to skewness, it is worth noting the strongly increasing value of variable X_7, which represents the number of tourists using accommodation per 1,000 people.

Rankings of Polish provinces

Two methods of linear ordering were used to calculate the level of socio-economic development of Polish provinces for selected years in the 2005-2020 time period: standardized sum method (7) and Hellwig's development pattern (10). The results are shown in Table 3 and presented in alphabetical order in terms of the names of the provinces. Descriptive characteristics of the synthetic measure of development calculated by the indicated methods are presented in Table 4.

Table 3. Level of socio-economic development according to synthetic measures of standardized sums and Hellwig's development pattern in 2005, 2010, 2017 and 2020

Province	2005		2010		2017		2020	
	M1	M2	M1	M2	M1	M2	M1	M2
dolnośląskie	0.588	0.560	0.636	0.602	0.699	0.676	0.683	0.652
kujawsko-pomorskie	0.329	0.280	0.344	0.299	0.331	0.293	0.326	0.282
lubelskie	0.292	0.247	0.316	0.282	0.311	0.275	0.322	0.267
lubuskie	0.376	0.313	0.336	0.283	0.388	0.309	0.387	0.295
łódzkie	0.469	0.402	0.488	0.432	0.485	0.427	0.494	0.404
małopolskie	0.610	0.530	0.632	0.545	0.634	0.564	0.590	0.546
mazowieckie	0.900	0.764	0.914	0.815	0.891	0.798	0.843	0.673
opolskie	0.341	0.259	0.401	0.335	0.377	0.325	0.388	0.309
podkarpackie	0.150	0.120	0.106	0.094	0.118	0.108	0.105	0.095
podlaskie	0.379	0.316	0.376	0.314	0.345	0.278	0.349	0.266
pomorskie	0.591	0.542	0.618	0.583	0.666	0.621	0.644	0.604
śląskie	0.516	0.460	0.524	0.476	0.480	0.444	0.489	0.429
świętokrzyskie	0.245	0.230	0.289	0.263	0.239	0.225	0.243	0.217
warmińsko-mazurskie	0.173	0.148	0.207	0.181	0.178	0.158	0.194	0.177
wielkopolskie	0.524	0.434	0.573	0.479	0.545	0.445	0.539	0.425
zachodniopomorskie	0.517	0.397	0.527	0.423	0.528	0.458	0.536	0.460

M1 – development level calculated by the standardized sum method,

M2 – development level calculated by the Hellwig development pattern method.

Source: own calculations

Table 4. Descriptive characteristics of the synthetic measure of development calculated by the standardized sum method and the Hellwig development pattern method

Parameter	2005		2010		2017		2020	
	M1	M2	M1	M2	M1	M2	M1	M2
mean	0.438	0.375	0.456	0.400	0.451	0.400	0.446	0.381
minimum	0.150	0.120	0.106	0.094	0.118	0.108	0.105	0.095
maximum	0.900	0.764	0.914	0.815	0.891	0.798	0.843	0.673
standard deviation	0.185	0.165	0.192	0.175	0.200	0.185	0.187	0.167
coefficient of variation [%]	42.39	43.88	42.22	43.74	44.25	46.24	42.02	43.78
range	0.750	0.644	0.807	0.721	0.773	0.690	0.738	0.578

M1 – development level calculated by the standardized sum method,

M2 – development level calculated by the Hellwig development pattern method.

Source: own calculations

The results highlight the high spatial differentiation of the level of socio-economic development in Poland. Analyzing the results, it can be said that regardless of the method chosen, the average value of the synthetic measure increased only when comparing the years 2005-2010, and when comparing the years 2010-2017 it was at the same level (Hellwig's development pattern method) or decreased (standardized sum method). In contrast, when considering 2017 and 2020, the average value of the synthetic measure decreased regardless of the method used. It is also important to note the range, the directions of change of which were the same with both methods used. When juxtaposing the years 2005 and 2010, its value increased, which means that the difference in the level of development between the province with the worst and the best score increased. Considering the years 2010, 2017 and 2020, with each successive analyzed year its value decreased, which can be considered a favorable phenomenon indicating the leveling of differences in development.

Based on the results obtained, a ranking of provinces was constructed for the four years under study. The ranking positions of individual provinces calculated using the standardized sum method are shown in Figure 2, and using the Hellwig development pattern method in Figure 3. The compatibility of the results obtained by both methods was checked by Spearman rank correlation.

Figure 2. Ranking of provinces by level of socio-economic development using the standardized sums method

Rank.	2005	2010	2017	2020
1	mazowieckie	mazowieckie	mazowieckie	mazowieckie
2	małopolskie	dolnośląskie	dolnośląskie	dolnośląskie
3	pomorskie	małopolskie	pomorskie	pomorskie
4	dolnośląskie	pomorskie	małopolskie	małopolskie
5	wielkopolskie	wielkopolskie	wielkopolskie	wielkopolskie
6	zachodniopomorskie	zachodniopomorskie	zachodniopomorskie	zachodniopomorskie
7	śląskie	śląskie	łódzkie	łódzkie
8	łódzkie	łódzkie	śląskie	śląskie
9	podlaskie	opolskie	lubuskie	opolskie
10	lubuskie	podlaskie	opolskie	lubuskie
11	opolskie	kujawsko-pomorskie	podlaskie	podlaskie
12	kujawsko-pomorskie	lubuskie	kujawsko-pomorskie	kujawsko-pomorskie
13	lubelskie	lubelskie	lubelskie	lubelskie
14	świętokrzyskie	świętokrzyskie	świętokrzyskie	świętokrzyskie
15	warmińsko-mazurskie	warmińsko-mazurskie	warmińsko-mazurskie	warmińsko-mazurskie
16	podkarpackie	podkarpackie	podkarpackie	podkarpackie

Source: own preparation

Figure 3. Ranking of provinces by level of socio-economic development using the Hellwig development pattern method

Rank.	2005	2010	2017	2020
1	mazowieckie	mazowieckie	mazowieckie	mazowieckie
2	dolnośląskie	dolnośląskie	dolnośląskie	dolnośląskie
3	pomorskie	pomorskie	pomorskie	pomorskie
4	małopolskie	małopolskie	małopolskie	małopolskie
5	śląskie	wielkopolskie	zachodniopomorskie	zachodniopomorskie
6	wielkopolskie	śląskie	wielkopolskie	śląskie
7	łódzkie	łódzkie	śląskie	wielkopolskie
8	zachodniopomorskie	zachodniopomorskie	łódzkie	łódzkie
9	podlaskie	opolskie	opolskie	opolskie
10	lubuskie	podlaskie	lubuskie	lubuskie
11	kujawsko-pomorskie	kujawsko-pomorskie	kujawsko-pomorskie	kujawsko-pomorskie
12	opolskie	lubuskie	podlaskie	lubelskie
13	lubelskie	lubelskie	lubelskie	podlaskie
14	świętokrzyskie	świętokrzyskie	świętokrzyskie	świętokrzyskie
15	warmińsko-mazurskie	warmińsko-mazurskie	warmińsko-mazurskie	warmińsko-mazurskie
16	podkarpackie	podkarpackie	podkarpackie	podkarpackie

Source: own preparation

The coefficient took the following values successively: 0.971 for the year 2005, 0.988 for the year 2010, 0.988 for the year 2017 and 0.976 for the year 2020. The results obtained show that the sequences obtained by the two methods are highly consistent. In both rankings in all analyzed years, the first place representing the highest level of socio-economic development in terms of the selected set of variables was occupied by the Mazowieckie province, and the last three positions went to the Świętokrzyskie, Warmińsko-Mazurskie and Podkarpackie provinces. The remaining 12 provinces were characterized by shifts in ranking position up or down by one, two or three positions. A decrease or increase in a province's position by k places was called a change by k position units for the purpose of discussing the results of the study. In both rankings, the changes of all provinces in all years totaled 22 positional units, despite the different temporal distribution. The most changes in positional units were observed when comparing 2010 and 2017, which may be due to a longer period (7 years) than when comparing 2005 and 2010 (5 years) and 2017 and 2020 (3 years). In addition to the Mazowieckie province, the highest positions were achieved by the Dolnośląskie, Pomorskie and Małopolskie provinces.

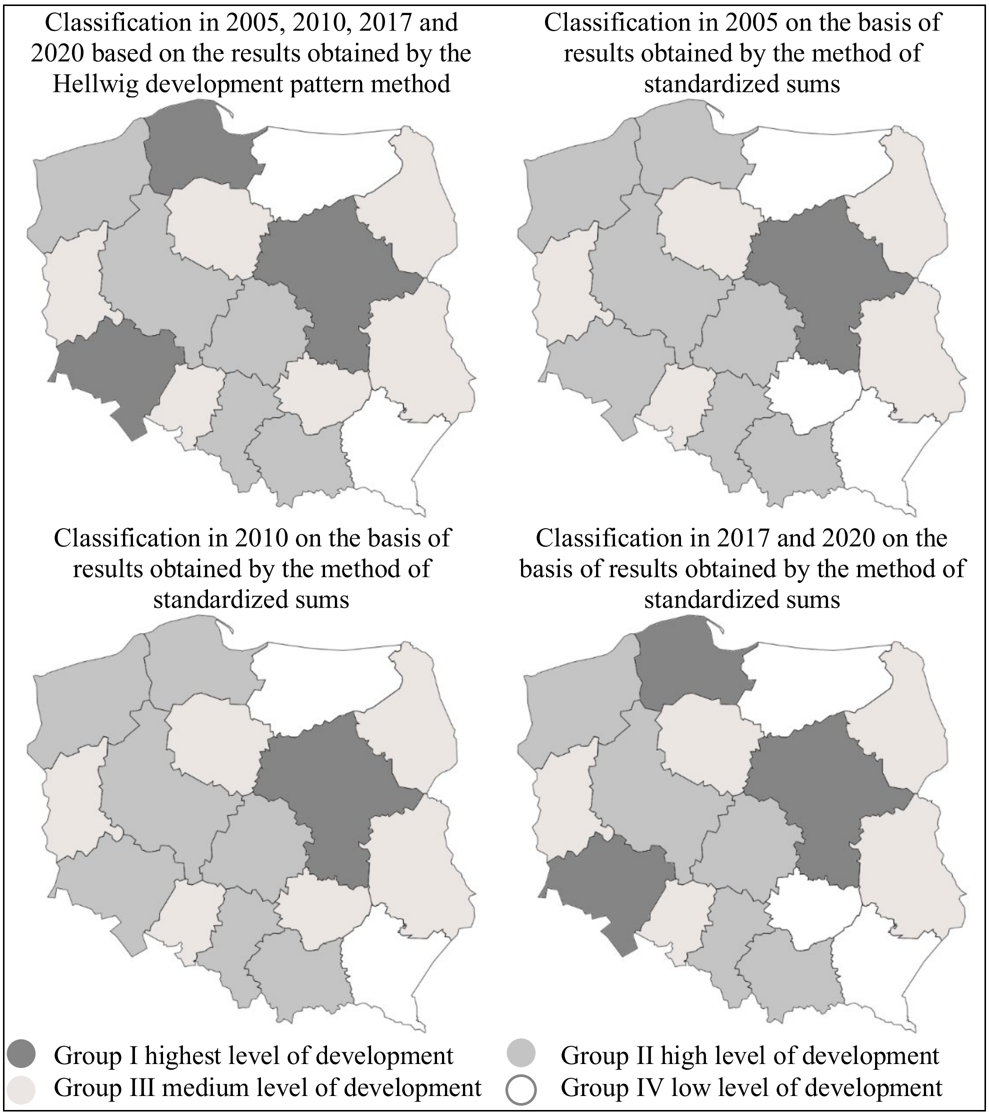
It is worth noting the Lubuskie province, which in the ranking made using results obtained by the method of standardized sums, was the only one to change its position by three position units (comparing 2010 and 2017), changing its place from 12 to 9. In the ranking made using results obtained by the method of Hellwig's development pattern, a change in position by three position units was observed with two provinces – Opolskie province, which between 2005 and 2010 changed its place from 12 to 9, and Zachodniopomorskie province, which was promoted from place 8 to 5.

Classification of Polish provinces

The provinces were assigned to four groups with similar levels of development considering the methods used. Spatial differentiation of provinces taking into account the achieved level of socio-economic development calculated by two methods is shown in Figure 4.

In the classification based on calculating the synthetic measure using Hellwig's development pattern method, the composition of the groups in all the years analyzed was unchanged, and the group with the highest level of socio-economic development (group I) included the Mazowieckie, Dolnośląskie and Pomorskie provinces. More restrictive in this regard was the classification based on the method of standardized sums, which assigned a smaller number of provinces to the group with the highest level of development and a larger number to the group with a low level of development (group IV). Only Mazowieckie province qualified for group I in 2005 and 2010, while three provinces were assigned to group IV except in 2005. On the other hand, in the classification based on Hellwig's development pattern method, only two provinces qualified for group IV: Warmińsko-Mazurskie and Podkarpackie provinces.

Figure 4. Spatial differentiation of the level of socio-economic development



Source: own elaboration

DISCUSSION

As a result of the research, the intended purpose was achieved, which was to characterize the spatial differentiation of the level of socio-economic development of Polish provinces in 2005-2020, and to analyze and compare the results in relation to the selected two methods of linear ordering, as well as to classify provinces interms of the level of development achieved. The research conducted showed the existence of large disparities between regions, which is consistent with the results of other studies [Barska et al. 2022; Malina 2020; Rokicki 2016].

According to the results of the study, based on the selected set of variables in 2020, the highest socio-economic development regardless of the method used was characterized successively by Mazowieckie, Dolnośląskie, Pomorskie and Małopolskie provinces, while the worst was characterized by Podkarpackie, Warmińsko-Mazurskie and Świętokrzyskie provinces. The same ranking of the best provinces can be found in the conducted research on the socio-economic level in Polish provinces in 2020, in which the synthetic measure of the level of development was calculated using Hellwig's method on the basis of 21 diagnostic variables [Barska et al. 2022]. However, in the discussed studies, the order of provinces was different and they were Pomorskie, Małopolskie, Dolnośląskie and Mazowieckie provinces in turn. The provinces with the weakest level of development in the comparative study were Świętokrzyskie, Warmińsko-Mazurskie, and Lubuskie provinces, and Podkarpackie province was ranked only fourth, counting from the bottom. What seems surprising is the position of Lubuskie province, which in the 2020 survey conducted in this article was given a relatively high tenth position. However, it is worth noting that the same provinces were included in both lineups of the best sites.

SUMMARY

The article characterizes the level of socio-economic development of Poland's provinces in the years 2005, 2010, 2017, and 2020. This was the main objective of the study, which was achieved using a synthetic measure based on an existing but modified set of diagnostic variables. Analyzing the values of diagnostic variables, favorable trends of change were observed. The unfavorable changes with each successive year were a decrease in the average number of university students per 10,000 population, and in the comparison of 2017 and 2020 – a decrease in the number of tourists using accommodation per 1,000 people, which could be due to restrictions introduced as a result of the COVID-19 pandemic. Two methods of linear ordering were used to calculate the synthetic measure, i.e. the method of standardized sums and the method of Hellwig's development pattern. Based on the results, two rankings were created, in which the first place in terms of socio-economic development was consistently occupied by Mazowieckie province. Thus, the first research objective was achieved, which aimed to verify whether the Mazowieckie province ranked first in all the analyzed years. In the group of provinces with the highest level of development based on the selected set of variables, the Dolnośląskie, Pomorskie, and Małopolskie provinces were also distinguished. The last places were given to the Świętokrzyskie, Warmińsko-Mazurskie and Podkarpackie provinces.

The second and third research objectives were also achieved, thus accomplishing all the set goals. These objectives involved evaluating the differences and consistency of the constructed rankings results, as well as determining the similarities and differences in the classifications based on the selected methods. Despite the high consistency in the ordering of the Polish provinces obtained by the two methods used, their rankings and classification were shaped differently.

REFERENCES

Adamiec J. (2017) Polityka regionalna Unii Europejskiej. Studia BAS, 1(49), 63-85 (in Polish).

Barska A., Jędrzejczak-Gas J., Wyrwa J. (2022) Poland on the Path towards Sustainable Development – A Multidimensional Comparative Analysis of the Socio-Economic Development of Polish Regions. Sustainability, 14(16), 10319.

Bartkowiak R. (2010) Współczesne teorie ekonomiczne. Roczniki Nauk Rolniczych. Seria G, 97(2), 16-29 (in Polish).

Bartkowiak-Bakun N. (2015) Zróżnicowanie poziomu rozwoju społeczno-gospodarczego obszarów wiejskich województwa wielkopolskiego. Roczniki Naukowe Ekonomii Rolnictwa i Rozwoju Obszarów Wiejskich, 102(2), 7-13 (in Polish).

Bąk A. (2018) Analiza porównawcza wybranych metod porządkowania liniowego. Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu, 508, 19-28 (in Polish).

Chojnicki Z., Czyż T. (Eds.) (1991) Zróżnicowanie przestrzenne poziomu i warunków życia ludności. Biuletyn KPZK PAN, 153 (in Polish).

Churski P. (2012) Polityka regionalna w Unii Europejskiej i w Polsce. Rozwój Regionalny i Polityka Regionalna, 19, 14-54 (in Polish).

Dziekański P. (2014) Koncepcja wskaźnika syntetycznego oceny poziomu rozwoju gmin wiejskich województwa świętokrzyskiego w warunkach globalizacji. Zeszyty Naukowe Szkoły Głównej Gospodarstwa Wiejskiego w Warszawie. Problemy Rolnictwa Światowego, XXIV/3, 61-70 (in Polish).

Główny Urząd Statystyczny (2018) Działalność centrów kultury, domów kultury, ośrodków kultury, klubów i świetlic w 2017 r. (in Polish).

Gostkowski M., Graczyk A., Koszela G. (2019) Application of the Linear Ordering Methods to Analysis of the Agricultural Market in Poland, Metody Ilościowe w Badaniach Ekonomicznych, (20)3, 167-177.

Grabiński T., Wydymus S., Zeliaś A. (1982) Metody doboru zmiennych w modelach ekonometrycznych. Warszawa, Polskie Wydawnictwo Ekonomiczne (in Polish).

Hellwig Z. (1968) Zastosowanie metody taksonomicznej do typologicznego podziału krajów ze względu na poziom ich rozwoju oraz zasoby i strukturę wykwalifikowanych kadr. Przegląd Statystyczny, 4, 307-327 (in Polish).

Jajuga K. (1992) Elementy wielowymiarowej analizy porównawczej. [in:] Bartosiewicz S. (Ed.) Ekonometria z elementami programowania matematycznego i analizy porównawczej. Wrocław, Akademia Ekonomiczna, 221-271 (in Polish).

Johnston B., Kilby P. (1975) Agriculture and Structural Transformation: Economic Strategies in Late-Developing Countries. London, Oxford University Press.

Kisielińska J., Borkowski B., Czech K., Górska A., Koszela G., Krawiec M., Landmesser J., Ochnio L., Pietrych Ł., Pietrzykowski R., Wasilewska E., Zielińska-Sitkiewicz M. (2021)

Wielowymiarowa analiza danych w ekonomice rolnictwa. Warszawa, Wydawnictwo SGGW (in Polish).

Klaassen L. (1965) Area. Economic and Social Redevelopment. Guidelines for Programmes. Paris, Organisation for Economic Co-operation and Development.

Koszela G., Gostkowski M., Ochnio L., Kostoglou V. (2020) A Comparison of Logistics Infrastructure Development Level of European Union Countries using TOPSIS and VIKOR Methods. Zeszyty Naukowe Szkoły Głównej Gospodarstwa Wiejskiego w Warszawie. Ekonomika i Organizacja Logistyki, 5(1), 15-27.

Kudełko J. (2004) Poziom rozwoju społeczno-gospodarczego województw Polski. Zeszyty Naukowe Akademii Ekonomicznej w Krakowie, 651, 75-90 (in Polish).

Kutkowska B., Pilawka T., Rybchak V., Rybchak O. (2019) Zróżnicowanie poziomu rozwoju społeczno-gospodarczego obszarów wiejskich województwa dolnośląskiego w latach 2002 i 2010. Annals of the Polish Association of Agricultural and Agribusiness Economists, 21(2), 170-187 (in Polish).

Leibenstein H. (1957) Economic Backwardness and Economic Growth. Nowy Jork, Wiley.

Malina A. (2004) Ocena stopnia zróżnicowania rozwoju regionalnego Polski w latach 1998 –200. Zeszyty Naukowe Akademii Ekonomicznej w Krakowie, 666, 5-21 (in Polish).

Malina A. (2020) Analiza przestrzennego zróżnicowania poziomu rozwoju społeczno-gospodarczego województw Polski w latach 2005-2017. Nierówności Społeczne a Wzrost Gospodarczy, 61, 138-155 (in Polish).

Nurkse R. (1953) Problems of Capital Formation in Underdeveloped Countries. New York, Oxford University Press.

Roman M. (2018) Innowacyjność agroturystyki jako czynnik poprawy konkurencyjności turystycznej makroregionu Polski Wschodniej. Warszawa, Wydawnictwo SGGW (in Polish).

Rokicki T. (2016) The Diversification of the Social and Economic Development of Voivodeships in Poland. Economic and Regional Studies, 9(4), 39-52.

Rosenstein-Rodan P. (1943) Problems of Industrialization of Eastern and South- Eastern Europe. Economic Journal, 53(210), 202-211 (in Polish).

Rostow W. (1956) The Take-Off into Self-Sustained Growth. Economic Journal, 66, 25-48.

Stec M. (2004) Analiza porównawcza poziomu rozwoju społeczno-gospodarczego Polski na tle krajów Unii Europejskiej i krajów do niej kandydujących. Nierówności Społeczne a Wzrost Gospodarczy, 5, 9-22 (in Polish).

Strahl D. (Ed.) (1998) Taksonomia struktur w badaniach regionalnych. Wrocław, Wydawnictwo Akademii Ekonomicznej we Wrocławiu im. Oskara Langego (in Polish).

Thorbecke E. (2006) The Evolution of the Development Doctrine, 1950-2005. UNU-WIDER Research Paper, 2006/155, 1-37.

United Nations Development Programme (2022) Human Development Report 2021/2022. Uncertain Times, Unsettled Lives: Shaping our Future in a Transforming World.

Wawrzyniak D. (2015) Analiza porównawcza poziomu rozwoju infrastruktury technicznej województw polski z wykorzystaniem metod taksonomicznych. Metody Ilościowe w Badaniach Ekonomicznych, XVI/4, 181-190 (in Polish).

APPENDICES

Appendix 1. Descriptive characteristics of variables

Variable no.	Year	Descriptive measures					
		Mean	Median	Minimum	Maximum	Skewness	V
X_1	2005	2 321.60	2 221.33	2 081.76	3 227.04	2.44	11.80
	2010	3 181.44	3 109.88	2 877.43	4 279.55	2.26	10.67
	2017	4 217.73	4 133.04	3 802.98	5 523.65	2.05	9.85
	2020	5 174.03	5 032.13	4 707.81	6 581.81	1.76	9.09
X_2	2005	18.99	18.60	13.80	27.20	0.57	20.63
	2010	13.64	13.35	9.20	20.00	0.38	21.80
	2017	7.32	7.00	3.70	11.70	0.29	28.71
	2020	6.95	6.60	3.70	10.20	0.06	25.60
X_3	2005	31.16	32.90	20.00	44.60	0.06	21.30
	2010	32.78	34.70	23.60	46.10	0.13	20.62
	2017	35.88	38.15	24.90	49.60	0.10	21.27
	2020	38.25	39.30	26.80	50.20	0.03	19.93
X_4	2005	479.06	452.00	357.00	680.00	0.88	17.67
	2010	439.88	428.50	258.00	635.00	0.49	22.38
	2017	300.24	275.35	138.60	480.80	0.46	31.96
	2020	282.17	263.10	125.90	453.10	0.28	33.13
X_5	2005	691.56	618.00	352.00	1 270.00	0.92	38.33
	2010	678.50	579.00	289.00	1 572.00	1.83	45.98
	2017	544.50	446.50	161.00	1 404.00	1.69	55.55
	2020	508.50	402.00	169.00	1 347.00	1.84	58.12
X_6	2005	315.98	316.70	263.30	374.20	0.28	10.18
	2010	439.63	440.80	390.00	506.40	0.48	7.70
	2017	576.89	570.15	503.50	648.40	0.24	7.21
	2020	653.28	647.25	576.50	717.30	0.12	6.61
X_7	2005	397.85	331.62	180.17	764.05	0.74	41.94
	2010	481.95	390.21	220.44	862.37	0.59	36.74
	2017	740.71	576.23	425.71	1 447.47	1.18	41.15
	2020	421.20	338.12	222.23	836.43	1.14	44.62
X_8	2005	918.50	907.50	663.00	1 221.00	0.16	17.02
	2010	975.69	974.00	717.00	1 293.00	0.34	17.72
	2017	1 064.63	1 024.50	803.00	1 503.00	0.60	18.39
	2020	1 163.31	1 113.00	899.00	1 608.00	0.62	16.93

V – coefficient of variation.

Source: own calculations

QUANTITATIVE METHODS IN ECONOMICS
Volume XXIV, No. 1, 2023, pp. 47 – 56

THE VOLATILITY OF 10-YEAR GOVERNMENT BONDS IN THE PERIOD OF INCREASED ECONOMIC UNCERTAINTY

Maria Sadowska https://orcid.org/0000-0001-5143-398X
Faculty of Applied Informatics and Mathematics
Warsaw University of Life Sciences – SGGW, Poland
e-mail: s196199@sggw.edu.pl

Abstract: Within the scope of this paper is to investigate the dynamic correlation and the volatility of 10-year sovereign bond yields in the G7 countries from January 4, 2010 to December 30, 2022. The following analyses were performed by dividing the said period into two sub-periods taking August 2, 2019 as a breaking point. Conclusions were made based on built VAR models. Conducted research indicates the USA as having the most significant influence on the rest of countries. European countries are perceived as more vulnerable to the external impact in shaping their bond yields. There are noticeable changes taking place in Italy between analyzed two periods – quotes become more dependent on other countries over time.

Keywords: government bond yields, VAR models, variance decomposition

JEL classification: C10, C58, E44

INTRODUCTION

The existence of the G7 group has been formally initialized in 1975 during their first meeting in France, at first as an answer for global economic problems, which had their origins in collapse of the Bretton Woods system and oil crisis. The group consists of seven countries placed all over the world: the United States of America, Canada, Germany, Italy, France, the United Kingdom and Japan, which are perceived as global economic powerhouses. Their undoubted authority in the international arena is coterminous with the influence on the other countries.

The key indicators of the functioning of the internal market are sovereign bond yields. The bond trading constitutes a one of the form of financing government spending and, at the same time, they are the safest way for depositing funds of traders. The dependence on government, identified with security, and high level of

https://doi.org/10.22630/MIBE.2023.24.1.3

availability for every investor reflect the factual economic situation of the domestic market evaluated from various perspectives (both from the perspective of the government and investors).

This paper aims at investigating intra-group impact on individual members of the G7 group in the context of changes that came into being with the appearance of COVID-19 pandemic. Above-mentioned influence is measured with examination of the state of the domestic economies, here represented by 10-year government bond yields. However, the period recognized as the beginning of the pandemic is generally defined as a moment with increased investor uncertainty – it is not only COVID-19, but historically high levels of inflation noted in most countries or political and military conflicts affecting decisions in the international arena as well.

LITERATURE REVIEW

The scientific research on intra-group impact in the G7 group in general is a frequent issue for the consideration of scholars from all over the world. This results in giving numerous approaches to the problem considering their financial markets, oil markets, stock markets and others. Studies have also been conducted in a view of significant economic transitions that the world underwent after turning points such as COVID-19 or crises (for example: crash of 2008).

Abakah EJA et al. [2021] aim at investigating the 10-year sovereign bond yields for entities from G7 group, Australia and Eurozone based on the data from January 1970 to February 2019. The analyses were carried out by ARMA-GARCH based pair copula models. The bond markets in Europe are found to have relatively low intrinsic interdependence. In their research, the authors cited previous publications that yielded similar results within the context of interconnectivity of German and the USA sovereign bond yields (weak effect). Finally, the paper also points out the implications for the investors value of this analysis such as strategic diversification of investments or understanding the determinants of macroeconomic policies.

Nasir M. A. et al. [2023] examine the independence of 10-year government bond yields noted in the G7 and the E7 countries. The data, they are analyzing in their research, includes daily quotes noted between December 31, 2019 and August 7, 2020. The authors use the TVP-VAR (time-varying-parameter-vector autoregression) model to study the static and dynamic connectedness. The results highlight the United States leadership in connectedness among the group and strong interdependence between all of the G7 countries. This paper concludes on the advantage of the dynamic approach over the static one in modeling the volatility of bond yields.

Lee H. et al. [2018] investigate the connectedness in G7 countries in house market volatility. The results are built considering VAR models and indicate rather low interdependence. They reveal the USA (especially during the GFC) and Italy (particularly during the European debt crisis) as having the highest net connectedness to other countries. This paper points out the relationship between Italy and France and strong general interdependence between European countries (from G7 group).

The main objective of this paper is an attempt to investigate the volatility of 10-year government bond yields in G7 countries over the period of increased economic uncertainty. Unlike most recently conducted research, this one focuses not only on changes caused by COVID-19 but examines a longer period following 2020. Thus allow to evaluate following changes in the long run thereby excluding short-term market jitters.

DATA AND METHODOLOGY

Methodology

In order to examine the intra-group influences in the G7 countries on 10-year sovereign bond yields there were VAR models built. The next steps were to analyze the variance decomposition and compare it with previously calculated values of correlation to finally build the impulse responses graphs.

VAR models (Vector Autoregressive Models) were firstly presented in 1980 by Sims as an answer for the high level of complication of the large-scale simultaneous equations structural models (Brooks, 2008). Thus appears basic assumption of such models – their ease-of-use and the simplicity to adjustment the model in line with to the various problems. The basic VAR model with the one lag and two variables ($y_1$and y_2) has a form of equations:

$$y_{1t} = \beta_{10} + \beta_{11}y_{1t-1} + \alpha_{11}y_{2t-1} + u_{1t} \quad (1)$$

$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} + \alpha_{21}y_{1t-1} + u_{2t} \quad (2)$$

where β_{10} and β_{20} stand for the constants in the equations and u_{1t}, u_{2t} for error terms. One of the most important stage of building the VAR models, determining the further conclusions, is the correct choice of the number of lags in equations. Thus in this article in order to build such models information criteria has been used. The main limitation of the VAR models, determining further results of statistical tests, is the stationarity of time series. Mentioned stationarity is examined by such statistical tests as KPSS (Kwiatkowski–Phillips–Schmidt–Shin) (Kwiatkowski D. et al., 1992) or ADF (augmented Dickey–Fuller test) which is an augmented version of Dickey-Fuller test (Dickey D. et al., 1979).

Variance decomposition allows to identify the relation of movements caused by internal changes to the ones caused by external movements. This constitutes a tool for getting extra analysis on the basis of built VAR models. Unlike the correlation matrix, this analyzes consider time-series not only as a stochastic data, but their relationship over time.

Impulse responses, on the other hand, indicates to what extend the internal market reacts to the shocks appearing on the rest of the markets. This analysis is based on the approach of the VMA models (vector moving average) being an expression of built VAR models.

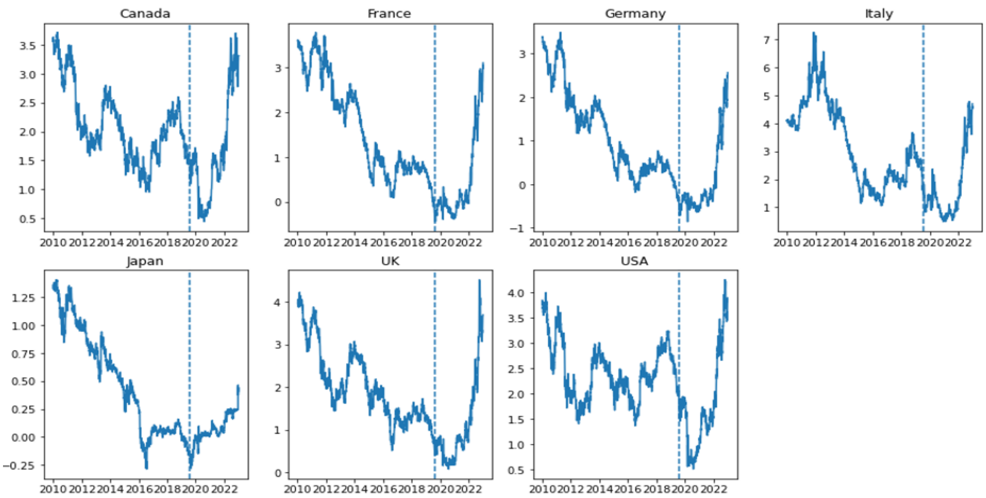
Data

The analysis concerns the data based on daily records of the 10-year bond quotes noted for the G7 countries (the USA, Canada, Germany, Italy, France, the UK and Japan). The data covers up the quotes recorded between January 4, 2010 and December 30, 2022 and consists of 2,971 records. All of the records were provided by https://stooq.pl/ and are expressed in percentages.

RESULTS

Within the scope of finding the breaking point the Bai-Perron test was carried out. Having slightly different results depending on the country, the date obtained for the USA was adopted as a global breaking point. The indicated date, determined as August 2, 2019, has been marked as dotted line in the figure below.

Figure 1. 10-year bond yields in G7 countries



Source: own calculations using Python 3.7

Hence, in the further analysis the separation for two sub-periods was made (the first one: January 4, 2010 to August 2, 2019, the second one: August 3, 2019 to December 30, 2022).

Table 1. Summary statistics, normality and stationarity tests for the first period (columns marked as 1) and the second period (columns marked as 2)

	Canada		France		Germany		Italy		Japan		UK		USA	
	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Mean	2.12	2.12	1.68	1.68	1.21	1.21	3.28	3.28	0.51	0.51	2.05	2.05	2.43	2.43
Median	2.02	2.02	1.31	1.31	0.95	0.95	2.95	2.95	0.51	0.51	1.86	1.86	2.38	2.38
Variance	0.41	0.41	1.19	1.19	1.00	1.00	2.16	2.16	0.21	0.21	0.74	0.74	0.30	0.30
Stand Dev	0.64	0.64	1.09	1.09	1.00	1.00	1.47	1.47	0.46	0.46	0.86	0.86	0.55	0.55
Coefficient of variation	0.20	0.20	0.88	0.88	1.10	1.10	0.76	0.76	0.53	0.53	0.41	0.41	0.13	0.13
Asymmetry	0.57	0.57	0.32	0.32	0.58	0.58	0.41	0.41	0.21	0.21	0.63	0.63	0.46	0.46
Kurtosis	-0.35	-0.35	-1.31	-1.31	-0.77	-0.77	-0.88	-0.88	-1.25	-1.25	-0.50	-0.50	-0.32	-0.32
Jarque_Bera	130.99	130.99	195.66	195.66	178.27	178.27	132.67	132.67	159.92	159.92	169.31	169.31	89.14	89.14
	Canada		France		Germany		Italy		Japan		UK		USA	
	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Jarque_Bera_p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
KPSS	3.40	3.40	6.67	6.67	6.43	6.43	4.93	4.93	7.04	7.04	5.33	5.33	1.02	1.02
KPSS_p	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
ADF	-2.36	-2.36	-2.43	-2.43	-2.45	-2.45	-1.86	-1.86	-2.79	-2.79	-2.62	-2.62	-2.53	-2.53
ADF_p	0.40	0.40	0.36	0.36	0.36	0.36	0.68	0.68	0.20	0.20	0.27	0.27	0.31	0.31
KPSS_diff	0.11	0.11	0.05	0.05	0.07	0.07	0.10	0.10	0.04	0.04	0.07	0.07	0.14	0.14
KPSS_diff_p	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

Source: own calculations using Python 3.7

The above calculations indicate similar distributions for all time-series (all countries in both periods). All data is characterized by other than normal distribution according to the Jarque-Bera test, although it should be noted that the Jarque-Bera test is sensitive to a large number of observation and there are 2,971 of them. The KPSS test indicates that all considered time-series are stationary at first differences.

Table 2. Correlation between 10-year bond yields for the first and the second periods

First period							
	Canada	France	Germany	Italy	Japan	UK	USA
Canada	1	0.776	0.856	0.533	0.750	0.871	0.857
France	0.776	1	0.974	0.856	0.965	0.868	0.422
Germany	0.856	0.974	1	0.748	0.960	0.936	0.545
Italy	0.533	0.856	0.748	1	0.797	0.545	0.144
Japan	0.750	0.965	0.960	0.797	1	0.890	0.394
UK	0.871	0.868	0.936	0.545	0.890	1	0.657
USA	0.857	0.422	0.545	0.144	0.394	0.657	1
Second period							
	Canada	France	Germany	Italy	Japan	UK	USA
Canada	1	0.921	0.923	0.854	0.731	0.934	0.978
France	0.921	1	0.997	0.965	0.808	0.975	0.932
Germany	0.923	0.997	1	0.954	0.805	0.979	0.940
Italy	0.854	0.965	0.954	1	0.703	0.921	0.874
Japan	0.731	0.808	0.805	0.703	1	0.763	0.681
UK	0.934	0.975	0.979	0.921	0.763	1	0.959
USA	0.978	0.932	0.940	0.874	0.681	0.959	1

Source: own calculations using Python 3.7

The above matrixes of correlation between 10-year bond yields show generally high values between stochastic data. But importantly, there is an overall increase in values in the second period compared to the first one which suggests an increase in intra-group influence.

In order to build VAR models, length of lags for both time periods were selected by using information criteria (Akaike, Schwartz-Bayesian, Hannan-Quinn Criteria). The obtained results for the first period indicate VAR(2) with two lags and for the second period as well VAR(2) as the ones with the lowest values of information criteria.

In order to build a VAR models, it is required for the time series to be stationary. Thus, the data was transformed into the first differences, which the KPSS test indicated as stationary.

Table 3. Model fit measures for VAR(2) for the first and the second periods

First period							
Parameters	Canada	France	Germany	Italy	Japan	UK	USA
R-squared	0.068	0.046	0.057	0.053	0.129	0.057	0.057
Adj. R-squared	0.057	0.029	0.040	0.036	0.114	0.041	0.041
sum sq. Resids	2.433	2.362	2.146	5.493	0.156	3.760	3.045
S.E. equation	0.057	0.056	0.054	0.086	0.014	0.071	0.064
Mean dependent	0.003	0.004	0.004	0.004	0.001	0.004	0.003
S.D. dependent	0.059	0.057	0.055	0.087	0.015	0.072	0.065
Second period							
Parameters	Canada	France	Germany	Italy	Japan	UK	USA
R-squared	0.068	0.046	0.057	0.053	0.129	0.057	0.057
Adj. R-squared	0.057	0.029	0.040	0.036	0.114	0.041	0.041
sum sq. Resids	2.433	2.362	2.146	5.493	0.156	3.768	3.045
S.E. equation	0.057	0.056	0.054	0.086	0.014	0.071	0.064
Mean dependent	0.003	0.004	0.004	0.004	0.001	0.004	0.003
S.D. dependent	0.059	0.056	0.055	0.087	0.015	0.072	0.065

Source: own calculations using Gretl

Building two separate VAR models for each period on the first differenced data resulted in slight differences while considering the above fit measures.

In order to examine the dynamic variance there was variance decomposition conducted and results were presented in Table 4. The order of countries used in the variance decomposition matrix was chosen based on the importance of their position in the G7 group. It has a significant meaning as the result of variance decomposition may differ depending on the adopted order of the variables.

Table 4. Variance decomposition for VAR(2) for the first period (columns tagged as 1) and the second period (columns tagged as 2)

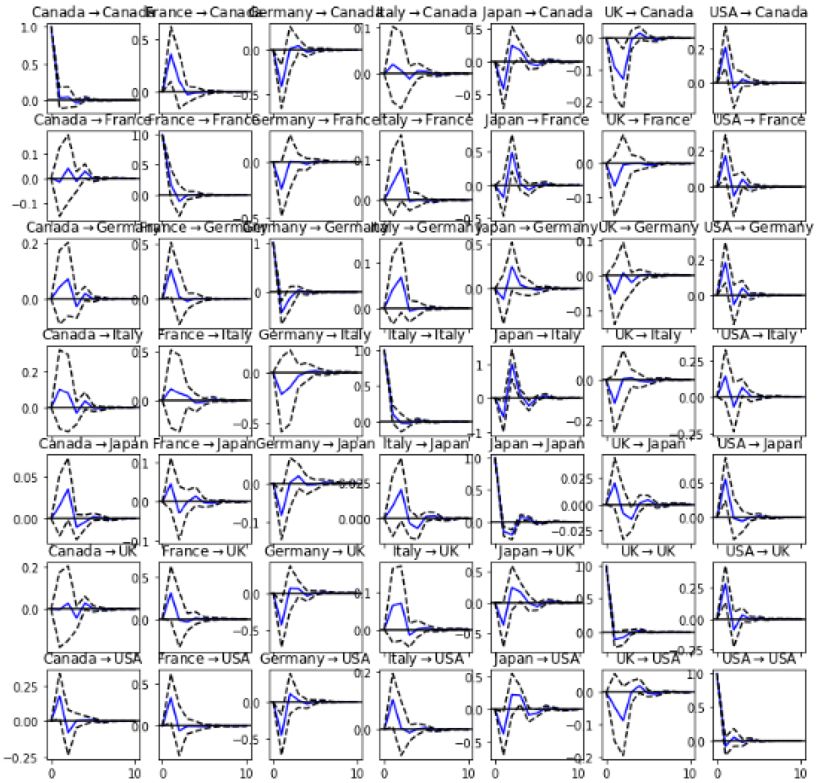
		Explained by:													
	Days	USA		UK		Japan		Italy		Germany		France		Canada	
PERIOD		1	2	1	2	1	2	1	2	1	2	1	2	1	2
USA	1	100.00	100.00	0	0	0	0	0	0	0	0	0	0	0	0
	2	99.62	95.42	0.16	0.01	0	0.38	0.03	2.58	0.06	0.37	0.03	0.67	0.10	0.58
	3	99.52	94.65	0.16	0.37	0.02	0.62	0.08	2.56	0.06	0.42	0.05	0.68	0.11	0.70
	5	99.52	94.38	0.16	0.38	0.02	0.87	0.08	2.56	0.06	0.44	0.05	0.67	0.11	0.70
	9	99.52	94.36	0.16	0.38	0.02	0.88	0.08	2.56	0.06	0.44	0.05	0.67	0.11	0.70
	10	99.52	94.36	0.16	0.38	0.02	0.88	0.08	2.56	0.06	0.44	0.05	0.67	0.11	0.70
UK	1	45.52	42.35	54.48	57.65	0	0	0	0	0	0	0	0	0	0
	2	45.52	41.75	54.11	55.91	0.01	0.40	0.06	0.90	0.08	0.60	0.18	0.44	0.04	0
	3	45.40	41.42	53.88	55.29	0.02	0.70	0.09	1.49	0.10	0.66	0.44	0.44	0.07	0.01
	5	45.37	41.35	53.87	55.18	0.02	0.79	0.11	1.52	0.10	0.67	0.45	0.44	0.08	0.05
	9	45.37	41.34	53.87	55.17	0.02	0.81	0.11	1.53	0.10	0.67	0.45	0.44	0.08	0.05
	10	45.37	41.34	53.87	55.17	0.02	0.81	0.11	1.53	0.10	0.67	0.45	0.44	0.08	0.05
Japan	1	3.58	7.87	0.91	0.06	95.52	92.07	0	0	0	0	0	0	0	0
	2	13.69	12.33	0.90	0.34	84.20	86.06	0	0.28	0.97	0.67	0.11	0.23	0.13	0.09
	3	13.56	11.86	1.04	0.34	83.71	85.74	0.07	0.59	0.97	0.67	0.26	0.29	0.38	0.49
	5	13.65	11.90	1.08	0.48	83.56	85.44	0.07	0.61	0.99	0.74	0.27	0.31	0.39	0.52
	9	13.65	11.90	1.08	0.49	83.55	85.42	0.07	0.61	0.99	0.75	0.27	0.31	0.39	0.53
	10	13.65	11.90	1.08	0.49	83.55	85.41	0.07	0.61	0.99	0.75	0.27	0.31	0.39	0.53
Italy	1	0.29	18.18	0	13.52	0.09	0.42	99.62	67.89	0	0	0	0	0	0
	2	0.51	18.24	0.66	13.39	0.14	1.06	98.32	67.06	0.02	0.10	0.33	0.05	0.02	0.11
	3	1.24	17.76	0.65	13.05	0.21	3.49	97.33	65.33	0.03	0.13	0.45	0.07	0.08	0.16
	5	1.25	17.85	0.70	13.00	0.22	3.61	97.26	65.13	0.04	0.13	0.46	0.08	0.08	0.19
	9	1.25	17.85	0.70	13.00	0.22	3.62	97.25	65.12	0.04	0.14	0.46	0.08	0.08	0.19
	10	1.25	17.85	0.70	13.00	0.22	3.62	97.25	65.12	0.04	0.14	0.46	0.08	0.08	0.19
Germany	1	44.47	51.10	21.59	14.80	0.11	0.46	0.03	4.59	33.80	29.05	0	0	0	0
	2	44.49	50.38	21.49	14.53	0.10	0.50	0.31	5.15	33.21	28.80	0.40	0.60	0.00	0.05
	3	44.45	49.67	21.40	14.39	0.11	0.95	0.42	5.68	32.96	28.53	0.65	0.60	0.02	0.17
	5	44.44	49.64	21.39	14.41	0.11	0.96	0.43	5.68	32.95	28.50	0.65	0.60	0.02	0.20
	9	44.44	49.64	21.39	14.41	0.11	0.96	0.43	5.68	32.95	28.50	0.65	0.60	0.02	0.20
	10	44.44	49.64	21.39	14.41	0.11	0.96	0.43	5.68	32.95	28.50	0.65	0.60	0.02	0.20
France	1	22.56	42.16	12.74	16.80	0.42	0.77	11.29	17.47	14.86	15.21	38.13	7.60	0	0
	2	23.13	41.98	13.12	16.70	0.41	0.90	11.40	17.63	14.74	15.12	37.17	7.67	0.03	0.01
	3	23.07	41.14	13.19	16.39	0.42	2.32	11.37	17.66	14.74	14.89	37.11	7.57	0.10	0.04
	5	23.05	41.17	13.22	16.36	0.42	2.35	11.39	17.63	14.73	14.87	37.08	7.56	0.10	0.07
	9	23.05	41.17	13.22	16.36	0.42	2.35	11.39	17.63	14.73	14.87	37.08	7.55	0.10	0.07
	10	23.05	41.17	13.22	16.36	0.42	2.35	11.39	17.63	14.73	14.87	37.08	7.55	0.10	0.07
Canada	1	64.90	69.96	5.21	2.41	0.05	0.16	0.02	0.38	0.54	2.45	0	0.01	29.28	24.63
	2	64.44	67.93	5.20	2.81	0.08	0.95	0.08	1.21	0.60	2.71	0.02	0.97	29.57	23.43
	3	64.40	66.84	5.20	3.09	0.08	1.44	0.08	1.52	0.65	2.97	0.03	1.04	29.55	23.10
	5	64.40	66.68	5.20	3.10	0.08	1.59	0.08	1.54	0.66	2.98	0.03	1.04	29.55	23.08
	9	64.40	66.66	5.20	3.10	0.08	1.61	0.08	1.54	0.66	2.98	0.03	1.04	29.55	23.07
	10	64.40	66.66	5.20	3.10	0.08	1.61	0.08	1.54	0.66	2.98	0.03	1.04	29.55	23.07
		USA		UK		Japan		Italy		Germany		France		Canada	
PERIOD		1	2	1	2	1	2	1	2	1	2	1	2	1	2

Source: own calculations using Gretl

The most independent country for both periods remains the USA and that is the only country that became less dependent on the other countries in the second period. There appeared significant dynamic changes of independence in Italy, which was initially one of the most unrelated to intra-group influences, to finally become dependent on bond yields in the USA and UK. The Japanese economy, taking account of its specific nature, continues to be independent with a small increase of the influence of the USA to its changes over time. In both periods it is possible to indicate the UK as the one modelling its economy on the actions of the USA market as dependence on the USA is nearly as high as the internal. There are strong external influences observed in France, Germany and Canada and each of these countries increased the level of external influences in the second period. The USA increased its influence in other countries over time, even though from the very beginning it was significant.

In order to analyze the impulse responses there were Orthogonal Impulse Responses used.

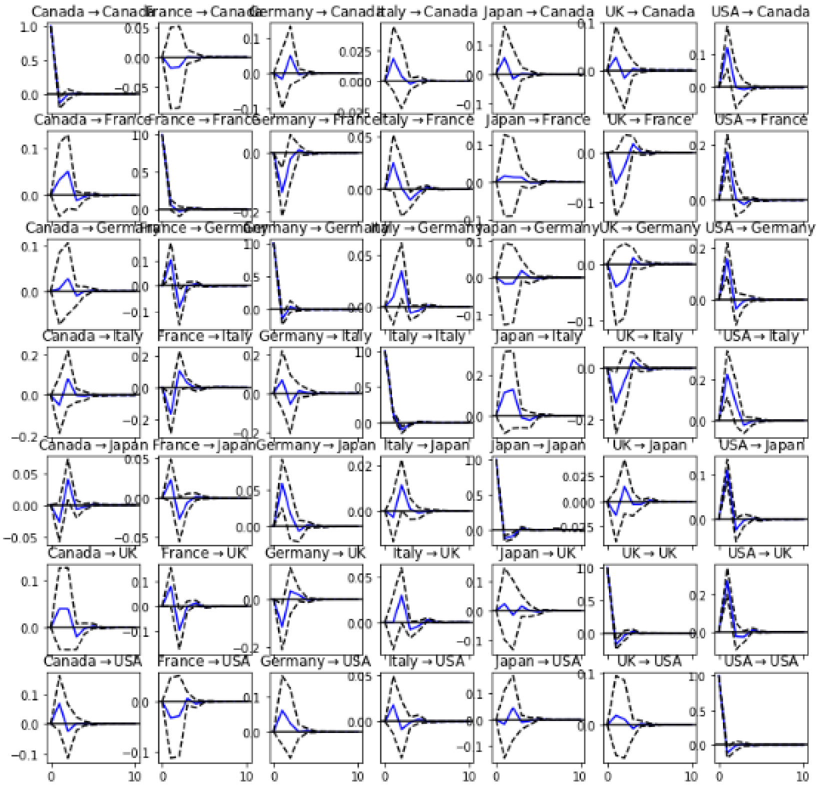
Figure 2. Impulse responses for VAR(2) for the first period



*A → B: shocks in country A causing the impulse responses in country B

Source: own calculations using Python 3.7

Figure 3. Impulse responses for VAR(2) for the second period



*A → B: shocks in country A causing the impulse responses in country B

Source: own calculations using Python 3.7

The structure of responses indicates the similarities in both periods with minor amendments. They are informing about reactions to the shocks in VAR models. Shocks on bond yields in the Germany significantly changed their influence on USA, Italy and Japan in the second period (now there are negative shocks vs. positive in the first one). There are noticeable changes in impulse responses in bond yields in Italy and Canada caused by France. Impulse responses occurring in the UK, Germany and France do not form a tendency to change the trend over time.

CONCLUSIONS

Aforementioned analysis investigates the volatility and dynamic correlation between 10-year sovereign bond yields in the G7 countries and changes taking place in the recent time. Conducted research stresses the fact of occurring interactions between bond markets in considered group. This study indicates USA as the most impacting on the rest of the G7 member economies in both periods. The most significant shifts are taking place in Italian economy – initially independent of intra-group influences, becomes increasingly dependent on other members (especially on the USA) over time. Japan is recognized as remaining in its strong independence over time with slight movements in the area of being impacted by the USA in the second period. Conducted analysis points out European countries as a group of being strongly impacted by others.

REFERENCES

Abakah E. J. A., Addo E., Gil-Alana L. A., Tiwari A. K. (2021) Re-Examination of International Bond Market Dependence: Evidence from a Pair Copula Approach. International Review of Financial Analysis, Elsevier, 74(C). https://doi.org/10.1016/j.irfa.2021.101678

Brooks C. (2008) Introductory Econometrics for Finance. 2. Cambridge University Press. https://doi.org/10.1017/CBO9780511841644

Dickey D. A., Fuller W. A. (1979) Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association, 74 (366), 427-431. https://doi.org/10.1080/01621459.1979.10482531

Helmut L. (2005) New Introduction to Multiple Time Series Analysis. Springer Books, Springer, number 978-3-540-27752-1.

Ihsan E. K., Semra K. (2017) Research of the Causalities US Stock Market Returns and G-7 Countries Stock Market Volatilities from Pre-Crisis to Post-Crisis of 2008. Advances in Management and Applied Economics, SCIENPRESS Ltd, 7(4), 33-42.

Kwiatkowski D., Phillips P. C. B., Schmidt P., Shin Y. (1992) Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root. Journal of Econometrics, 54, 159-178.

Krawiec M., Borkowski B., Shachmurove Y. (2022) Modeling Dynamic Correlation and Volatility of the Visegrad Group Fuel Markets. Available at SSRN: https://ssrn.com/abstract=4186709 or http://dx.doi.org/10.2139/ssrn.4186709

Lee H. S., Lee W. S. (2018) Housing Market Volatility Connectedness among G7 Countries. Applied Economics Letters, 25(3), 146-151. https://doi.org/10.1080/13504851.2017.1305069

Nasir M. A., Le T. N. L., Ghabri Y., Huynh L. D. T. (2023) Sovereign Bonds and Flight to Safety: Implications of the COVID-19 Crisis for Sovereign Debt Markets in the G-7 and E-7 Economies. International Review of Financial Analysis, Elsevier, 86(C). https://doi.org/10.1016/j.irfa.2023.102548

Sims C. A. (1980) Macroeconomics and Reality. Econometrica, 48(1), 1-48.