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Analyzing the Effects of Mobility and Season on COVID-19 Cases Using Negative Binomial Regression: a European Case Study

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Abstract—**This paper develops a Generalized Linear Model using the Negative Binomial Regression with log link function to analyze the effects of mobility trends and seasons on COVID-19 cases. The data of four European countries was used, namely Austria, Greece, Italy, and Czech Republic. The dataset includes daily observations of registered COVID-19 cases, and the data of six types of mobility trends: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential mobility for the period Feb 15 - Nov 15, 2020. The results suggest that the number of COVID-19 cases differs between seasons and different mobility trends.**

Keywords - negative binomial regression; COVID-19; statistical analysis; mobility trends; seasons

I. INTRODUCTION

The end of 2019 was marked by the occurrence of the first registered cases of SARS-CoV-2 (i.e. COVID-19) virus. The virus first emerged in Wuhan, China and has since then spread to 191 countries (data of December 06, 2020) [1]. On January 30, 2020 the World Health Organization (WHO) has announced global health emergency due to the rapid spread of the virus. The current number of coronavirus registered cases globally is 67.1 million with the highest number of cases reported in US (14.8 million), India (9.7 million), Brazil (6.6 million), Russia (2.5 million), and France (1.7 million) [1]. Globally, more than 1.5 million lost their battle against the novel coronavirus [1].

To stop the spread of the virus, most countries have imposed measures of social distancing, as well as travel and mobility restrictions. Several studies showed that the mobility restrictions limit the spread of novel coronavirus [2, 3, 4]. However, the mobility patterns may be a subject of influence of other non-imposed and rather natural factors such as meteorological conditions and season of the year. The authors in [5] used statistical models at the country level to research connections between human mobility and the spread of the virus during the beginning stage of the COVID-19 crisis. The indicators used in predicting the virus spread, following a diffusion pattern stretching beyond neighboring countries, and assisting in estimating the pandemic growth linked to travelers from Wuhan, China are: (i) travel volume data based on mobility corridors of migrant population in China as well as the population of Chinese origin in other countries, (ii) human development index, (iii) human freedom score, (iv) population size, (v) population density, and (vi) crude rate of virus spread. A study assumes a normal distribution of the cases diagnosed in Wuhan as well as that each resident of the Hubei province and anyone traveling from Wuhan have the same chance of being infected. A partial lockdown and contact restrictions were imposed in Germany during the March-May period of 2020. The authors in [6] observed that a relaxing of the restrictions in the latter period was not followed by the further increase in virus spread. This is an evidence of population behavioral changes influenced by contact restrictions. The authors in [7] developed a machine learning model based on human mobility patters and sociodemographic indicators for identifying the local level concentration of infected individuals in order to contain a virus spread within the vulnerable population groups of a large city such as Los Angeles, CA. In addition, researchers in [8] developed a model to simulate the virus spread in ten largest US cities and observed that: (i) restrictions to maximum occupancy are more effective than imposing a uniform reduction of mobility and (ii) higher infection rates amongst susceptible disadvantaged racial and socioeconomic groups could be contributed to visiting more crowded locations. The authors in [9] used multiple linear regression as predictive mining techniques to discover the effect of the socioeconomic, environmental, health care and mobility indicators on the virus spread in Italy during the end of the winter and spring of 2020. The research concluded that the virus spread is directly related to historical mobility habits (21 days prior), population density, particular matter (PM) pollution and number of administrated tests per day while it is inversely related to the temperature.

The current literature, however, does not consider the effects of seasonality on mobility trends and the spread of COVID-19. The mobility trends are highly dependent on many factors such as the weather, thus to be able to understand how different mobility trends impact the transmission of the virus, it is necessary to also observe the relationships between seasons.

This study investigates the effects of season and mobility trends on COVID-19 cases in four European countries by using Negative Binomial Regression (NBR). The countries used in the analysis are Italy, Czech Republic, Austria, and Greece. The reason for choosing these countries is because Italy and Czech Republic are representatives in terms of higher numbers of COVID-19 cases, while Greece and Austria have encountered fewer cases of infection. The novelty of this study can be demonstrated by the following: (i) the main effects between seasons and the number of COVID-19 registered cases were investigated, as well as the main effects between trends of six types of mobility, (ii) the interaction effects between seasons and mobility trends and their contribution to the number of COVID-19 cases were observed, (iii) a pairwise comparison was performed to obtain evidence of the difference in the number of COVID-19 cases between seasons.

This paper is structured as follows. Section II presents the data and utilized methodology, followed by Section III presenting and discussing the results. Finally, Section IV draws the conclusions of the research.

II. Data and Methodology

A. Data

The purpose of this research is to determine which mobility and seasonality factors play an important role in the occurrence of COVID-19 cases. The relationships between mobility factors, seasons, and COVID-19 cases were investigated using the NBR. For this study, the data of four countries was collected: Austria, Czech Republic, Greece, and Italy. The dependent variable is the number of COVID-19 cases per day, while continuous independent variables include mobility trends of six types of mobility: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential. The mobility data was obtained from Google Mobility data [10] and is represented by positive or negative trends in movement compared to the baseline day. The baseline day is the median of a 5-week period Jan 3 – Feb 6, 2020 [10]. The number of COVID-19 cases was obtained from Our World in Data [11]. Additionally, one categorical variable was formed – the seasons of the year (i.e., spring, summer, winter, and autumn), based on the dates of the samples in the dataset. The dataset included daily observations for a period February 15 to November 15, 2020.

B. Methodology

The dependent variable, COVID-19 cases, can be observed as a count variable hence the Poisson regression or NBR should be utilized. As the Poisson regression assumes that the mean of the variable should be equal to the variance, which here is not the case for every variable, the NBR is more suitable because it is more robust to this assumption.

The Negative Binomial distribution of the dependent variable can represent the number of trials needed to observe k successes and is suitable for variables with non-negative integer values.

The NBR with a log link function was used. The link function is a connection between the mean of the distribution function and the linear predictors. The Poisson regression and NBR use the log link function that can be represented as:

$$g(\mu) = \log(\mu).$$

For the parameter estimation a hybrid method was used which combines Fisher scoring [12] and Newton-Raphson scoring [13]. The method works by performing iterations using the Fisher scoring first, until the maximum number of iterations is reached. If the convergence is achieved before reaching the maximum number of iterations, the algorithm switches to the Newton-Raphson method.

The pairwise comparison between seasons and the number of COVID-19 cases was made based on the least significant difference.

All analyses were performed in SPSS v. 25.

III. Results and Discussion

The goodness of the fit measures in the Generalized Linear Model (GLM) shows the performance of the model. In particular, the ratio of the deviance value to the degrees of freedom should be as close to 1, otherwise if it is much higher than one, it indicates there is overdispersion; if it is much less than 1 it shows that there is underdispersion. The overdispersion represents the most frequent problem, so it is important to check this value first. All of the models obtained a deviance of around 1.2 which is acceptable.

In order to compare the models, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used. AIC [14] is a method based on in-sample fit to provide an estimate of likelihood of a model to make prediction/estimate of future values. A model is better if the AIC is minimum among all the other models. Also, BIC [15] is a second criteria for selection of the model that evaluates the trade-off between model fit and its complexity. A better fit is obtained by a lower BIC. One of the major differences between these two methods it that the AIC penalizes the complex models less than BIC [16]. Finally, the omnibus test is a likelihood-ratio chi-square test of the current model versus the null (in this case, intercept) model. The significance value of less than 0.05 indicates that the current model outperforms the null model.

The AIC and BIC show that the best GLM is the one for Greece, while the omnibus test shows that all the models are a significant improvement over a model without any predictor. These results are presented in Table 1.

TABLE I. GOODNESS OF THE FIT MEASURES

Country	Fit statistics				
	Deviance (value/df)	*Pearson's Chi Square (value/df)*	*AIC*	*BIC*	*Omnibus test sig.*
Austria	1.234	1.158	3317.681	3422.567	.000
Czech Republic	1.188	1.309	3460.497	3565-384	.000
Greece	1.259	1.006	2882.133	2986.808	.000
Italy	1.271	1.266	4356.118	4461.005	.000

The NBR coefficients (β), along with the standard error (SE), and exponentiated β are presented in Table 2 for each of the countries for the main effects, while the investigated interaction effects are presented in Table 3, followed by the pairwise comparison of differences in COVID-19 registered cases between seasons, for the selected countries.

A. Main effects

For Austria, it can be observed that the spring is not a significant variable, but the summer, autumn, and winter are. Compared to the winter season, which was chosen as a reference category, the log count of COVID-19 cases in summer increases by 4.683, while the log count of COVID-19 cases in autumn increases by 4.704 The variables retail, grocery, transit, and residential are all statistically significant with coefficients of 0.135, 0.054, -0.439, and -0.770 respectively. This means that for every one-unit increase in retail mobility trends, the expected log count of the number of COVID-19 cases increases by 0.135. Additionally, for every one-unit increase in grocery mobility trends, the expected log count of the number of COVID-19 cases increases by 0.054. Considering transit stations, for every one-unit increase in transit mobility trends, the expected log count of the number of COVID-19 cases decreases by 0.439 cases. Lastly, for every one-unit increase in residential mobility trends, the expected log count of the number of COVID-19 cases decreases by 0.770. The last category of season – winter, is a reference group with an exponentiated value of 1.

Differently, for the Czech Republic, it can be observed that that spring, summer, and autumn are all significant predictors. Compared to the winter season, the log count of COVID-19 cases in autumn increases by 8.56, while the log count of COVID-19 cases in spring increases by 4.468. In summer, the number of COVID-19 cases increases by 6.909 compared to the winter season. All the mobility variables except grocery and pharmacy mobility trends are significant predictors. Considering retail and recreation mobility trends, it can be observed that for every one-unit increase in retail mobility trends, the expected log count of the number of COVID-19 cases increases by 0.152. Additionally, for every one-unit increase in parks mobility trends, the expected log count of the number of COVID-19 cases increases by 0.047. Considering transit stations, for every one-unit increase in transit mobility trends, the expected log count of the number of COVID-19 cases decreases by 0.465 cases. Additionally, for every one-unit increase in workplaces mobility trends, the expected log count of the number of COVID-19 cases increases by 0.421. Lastly, for every one-unit increase in residential mobility trends, the expected log count of the number of COVID-19 cases increases by 0.403.

As for the Czech Republic, for Greece, all the seasons are significant predictors of the model. Compared to the winter season, the log count of COVID-19 cases in summer increases by 6.679, the log count of COVID-19 cases in autumn increases by 8.588, while the log count in spring increases by 3.357. The mobility trends variables, particularly grocery and pharmacy mobility, workplaces, and residential mobility were found to be statistically significant predictors, with coefficients of 0.075, 0.369, and 0.963, respectively. This means that for every one-unit increase in grocery and pharmacy mobility trends, the expected log count of the number of COVID-19 cases increases by 0.075. Additionally, for every one-unit increase in workplace mobility trends, the expected log count of the number of COVID-19 cases increases by 0.369. Considering residential mobility trends, for every one-unit increase the expected log count of the number of COVID-19 cases increases by 0.963 cases.

Finally, also for Italy, it can be observed that all the seasons are significant predictors of the model. Compared to the winter season, the log count of COVID-19 cases in summer increases by 7.771, the log count of COVID-19 cases in autumn increases by 4.960, while the log count in spring increases by 1.991. The mobility trends variables, particularly grocery and pharmacy mobility, and transit stations mobility are found to be statistically significant predictors, with coefficients of 0.066 and -0.197, respectively. This means that for every one-unit increase in grocery and pharmacy mobility trends, the expected log count of the number of COVID-19 cases increases by 0.066. Additionally, for every one-unit increase in transit stations mobility trends, the expected log count of the number of COVID-19 cases decreases by 0.197.

B. Interaction effects

The observed interaction effects included the analysis of the interaction between seasons, different types of mobility trends, and COVID-19 cases (Table 3).

Considering the spring season, we can see that retail and recreation mobility trends in spring have a negative relationship with the COVID-19 cases in Austria and Czech Republic, but a positive relationship with the COVID-19 cases in Greece, while for Italy no significant effect was found. For Austria, an increase in one-unit of retail and recreation mobility trends in spring decreased the number of COVID-19 cases by 12.9%, compared to the winter. In Greece, an increase in retail and recreation mobility trends in spring increased the number of COVID-19 cases by 8.8%, compared to the winter. In Czech Republic, an increase in retail and recreation mobility trends in spring decreases the number of COVID-19 cases by 14.8%, compared to the winter. Considering the grocery and pharmacy mobility trends in spring, for all (statistically significant countries) it was found that an increase in grocery and pharmacy trends decreases the number of COVID-19 cases by 4.2% (Austria), 7.4% (Greece) and 5.6% (Italy), compared to the winter season. Considering the parks mobility in spring, statistically significant effects were found only for the Czech Republic, indicating that an increase in parks mobility trends leads to a decrease of COVID-19 cases by 4.4%, compared to the winter. The transit stations mobility is found to increase the number of COVID-19 cases, in particular in Austria by 43.5%, in Italy by 18.8%, and in Czech Republic by 56.4%, compared to the winter. The workplace mobility trends were found to decrease the number of COVID-19 cases in spring in Greece and Czech Republic, by 29.7% and 33.9%, respectively, compared to the winter season. Finally, it was found that during the spring the number of COVID-19 cases increased by more than double in Austria as residential mobility trends increased. On the contrary, in Greece and Czech Republic the increase in residential mobility trends during the spring decreased the number of COVID-19 cases by 62.5% and 31.3%, respectively.

During the summer it was found that the increase in retail and recreation mobility trends increases the number of COVID-19 cases in Italy by 8.1% but decreases in Czech Republic by 18.3%, compared to the winter. Additionally, an increase in grocery and pharmacy mobility trends decreased the number of COVID-19 cases by 8.3% (Austria), 6.5% (Greece), and 11.7% (Italy), compared to the winter. Parks mobility trends were a significant predictor for Czech Republic, where it showed that an increase in parks mobility trends decreases the number of COVID-19 cases by 4.7%, compared to the winter. The transit stations mobility was found to increase the number of COVID-19 cases for all the four countries. Additionally, an increase in workplace mobility trends decreases the COVID-19 cases in Greece and Czech Republic by 35.7% and 36.4%, respectively, while the increase in residential mobility trends decreased the number of COVID-19 cases in Greece (by 52.9%) and Czech Republic (by 32.2%), and increased the number of cases in Italy by 56%, compared to the winter season.

Finally, in autumn the increase in retail and recreation mobility trends decreased the number of COVID-19 cases in Austria and Czech Republic by 13.7% and 16.2%, respectively, compared to the winter. The increase in grocery and pharmacy mobility trends decreased the number of COVID-19 cases in Greece by 5.9%, compared to the winter. The increase in parks mobility trends decreased the number of COVID-19 cases in Czech Republic by 4%, while the increase in transit stations mobility trends increased the number of COVID-19 cases in Austria, Italy, and Czech Republic, compared to the winter. Finally, the increase in workplace mobility trends led to a decrease of COVID-19 cases in Greece (by 31.3%) and Czech Republic (by 30.9%), compared to the winter season, while the increase in residential mobility trends increased the number of COVID-19 cases in Austria, but decreased it in Greece, compared to the winter season.

C. Pairwise comparison between seasons and the number of COVID-19 cases

As significant differences were found between seasons (while using winter as a reference category) and the number of COVID-19 cases, these differences were compared (Table 4).

From Table 4, it can be observed that statistically significant differences in number of COVID-19 cases have been found between spring and autumn, hence the number of COVID-19 cases is lower in spring than in autumn for Austria, Czech Republic, and Italy, while for the Greece there was not enough evidence to make such conclusions. For Czech Republic and Greece, it was also found that the number of COVID-19 cases is higher in spring than in winter. Additionally, for the Greece it was found that the number of COVID-19 cases was lower in spring than in summer.

For all the four countries enough evidence was found to conclude that the number of COVID-19 cases was lower in summer than in autumn. Additionally, for Czech Republic and Greece it was found that the number of COVID-19 cases was higher in summer than in winter. For Greece, the number of COVID-19 cases is also higher in summer than in spring.

It was further observed that the number of COVID-19 cases statistically differs between autumn and summer for Czech Republic, Austria, and Italy. Here, the number of COVID-19 cases is higher in autumn than in summer. Additionally, the number of COVID-19 cases is higher in autumn than in spring, but also higher than in winter for Czech Republic, Greece, and Italy. Lastly, the number of COVID-19 cases in winter was found to be significantly lower than in other seasons. These results suggest that the number of COVID-19 registered cases is higher in autumn than in the spring, summer, or winter, but the reason for such difference should be further investigated. It should be noted, however, that in the winter and spring seasons the rise of new cases was considered as a 'first wave' of the pandemic, while the surge in new cases during the autumn is considered as a 'second wave'.

The overall Wald Chi-Square statistics is significant at the 0.01 level, indicating that the model effects are statistically significant [17].

TABLE II. MAIN EFFECTS IN THE NBR MODEL

Main effects[b]	Austria			Czech Republic			Greece			Italy		
	β	*SE*	*EXP(β)*	*β*	*SE*	*EXP(B)*	*β*	*SE*	*EXP(β)*	*β*	*SE*	*EXP(β)*
Spring	0.581	0.628	1.788	**4.468**[a]	0.434	87.182	**3.357**[a]	0.781	28.703	**1.991**[a]	0.873	7.323
Summer	**4.683**[a]	0.567	108.094	**6.909**[a]	0.571	1001.246	**6.579**[a]	0.643	719.819	**7.771**[a]	0.569	2370.841
Autumn	**4.704**[a]	0.493	110.388	**8.560**[a]	0.497	5218.681	**8.588**[a]	0.918	5366.869	**4.960**[a]	0.525	142.594
Winter – ref. category			1			1			1			1
Grocery and pharmacy	**0.054**[a]	0.016	1.055	0.049	0.028	1.050	**0.075**[a]	0.026	1.078	**0.066**[a]	0.020	1.068
Parks	-0.009	0.014	0.991	**0.047**[a]	0.019	1.048	0.001	0.016	1.001	0.017	0.015	1.017
Retail and recreation	**0.135**[a]	0.046	1.145	**0.152**[a]	0.054	1.164	-0.055	0.031	0.946	-0.018	0.016	0.982
Transit stations	**-0.439**[a]	0.069	0.645	**-0.465**[a]	0.139	0.628	**-0.035**[a]	0.046	0.966	**-0.197**[a]	0.022	0.821
Workplaces	-0.108	0.077	0.898	**0.421**[a]	0.127	1.523	**0.369**[a]	0.078	1.446	0.059	0.055	1.061
Residential	**-0.770**[a]	0.240	0.463	**0.403**[a]	0.162	1.496	**0.963**[a]	0.248	2.620	-0.126	0.096	0.882

[a] Statistically significant.
[b] Dependent variable – number of COVID-19 cases

TABLE III. INTERACTION EFFECTS IN THE NBR MODEL

Interaction Effects[b]		Austria			Greece			Italy			Czech Republic		
Season	***Mobility trend***	*β*	*SE*	*EXP(β)*	*β*	*SE*	*EXP(β)*	*β*	*SE*	*EXP(β)*	*β*	*SE*	*EXP(β)*
Spring	Retail and recreation	**-0.138**[a]	0.048	0.871	**0.084**[a]	0.034	1.088	-0.009	0.020	0.991	**-0.160**[a]	0.055	0.852
	Grocery and pharmacy	**-0.043**[a]	0.017	0.958	**-0.077**[a]	0.026	0.926	**-0.058**[a]	0.021	0.944	-0.042	0.029	0.959
	Parks	0.012	0.015	1.012	-0.005	0.017	0.995	-0.017	0.016	0.983	**-0.045**[a]	0.020	0.956
	Transit stations	**0.361**[a]	0.075	1.435	-0.032	0.054	0.969	**0.172**[a]	0.038	1.188	**0.447**[a]	0.139	1.564
	Workplaces	0.140	0.078	1.150	**-0.353**[a]	0.081	0.703	-0.053	0.058	0.948	**-0.414**[a]	0.127	0.661
	Residential	**0.821**[a]	0.241	2.273	**-0.980**[a]	0.255	0.375	0.138	0.100	1.148	**-0.376**[a]	0.165	0.687
Summer	Retail and recreation	-0.080	0.049	0.923	0.016	0.034	1.016	**0.078**[a]	0.025	1.081	**-0.202**[a]	0.058	0.817
	Grocery and pharmacy	**-0.087**[a]	0.019	0.917	**-0.067**[a]	0.027	0.935	**-0.124**[a]	0.027	0.883	-0.033	0.041	0.968
	Parks	-0.006	0.014	0.994	-0.004	0.017	0.996	-0.025	0.015	0.975	**-0.048**[a]	0.020	0.953
	Transit stations	**0.458**[a]	0.074	1.581	**0.183**[a]	0.055	1.201	**0.390**[a]	0.034	1.477	**0.596**[a]	0.140	1.815
	Workplaces	0.029	0.078	1.029	**-0.441**[a]	0.081	0.643	-0.084	0.056	0.919	**-0.452**[a]	0.128	0.636
	Residential	0.328	0.255	1.388	**-0.753**[a]	0.261	0.471	**0.445**[a]	0.125	1.560	**-0.390**[a]	0.175	0.677
Autumn	Retail and recreation	**-0.147**[a]	0.048	0.863	0.062	0.041	1.064	-0.050	0.031	0.951	**-0.177**[a]	0.056	0.838
	Grocery and pharmacy	-0.027	0.020	0.973	**-0.061**[a]	0.028	0.941	0.009	0.032	1.009	-0.044	0.029	0.957
	Parks	0.015	0.015	1.015	-0.026	0.018	0.974	0.002	0.018	1.002	**-0.041**[a]	0.020	0.960
	Transit stations	**0.358**[a]	0.072	1.430	0.026	0.059	1.026	**0.120**[a]	0.049	1.127	**0.471**[a]	0.141	1.602
	Workplaces	0.124	0.080	1.132	**-0.376**[a]	0.084	0.687	0.048	0.061	1.049	**-0.369**[a]	0.129	0.691
	Residential	**0.818**[a]	0.249	2.266	**-0.981**[a]	0.275	0.375	0.233	0.157	1.262	-0.245	0.180	0.783

[a] Statistically significant.
[b] Dependent variable – number of COVID-19 cases

TABLE IV. PAIRWISE COMPARISON BETWEEN SEASONS

		Austria		Greece		Italy		Czech Republic	
Season (I)	***Season (J)***	***Mean difference (I-J)***	***SE***	***Mean difference (I-J)***	***SE***	***Mean difference (I-J)***	***SE***	***Mean difference (I-J)***	***SE***
Autumn	Spring	**2767.07**[a]	448.237	**464.62**[a]	113.443	**8942.25**[a]	2286.171	**3252.02**[a]	574.663
	Summer	**2772.87**[a]	448.269	242.68	150.512	**8911.94**[a]	2293.558	**3118.81**[a]	580.643
	Winter	1547.44	1307.116	**478.24**[a]	113.428	**8779.96**[a]	2305.219	**3316.20**[a]	574.609
Spring	Autumn	**-2767.07**[a]	448.237	**-464.62**[a]	113.443	**-8942.25**[a]	2286.171	**-3252.02**[a]	574.663
	Summer	5.79	6.932	**-221.94**[a]	98.952	-30.32	195.531	-133.20	83.870

	Winter	-1219.63	1227.866	**13.62**[a]	1.932	-162.29	303.086	**64.18**[a]	7.985
Summer	Autumn	**-2772.87**[a]	448.269	-242.68	150.512	**-8911.94**[a]	2293.558	**-3118.81**[a]	580.643
	Spring	-5.79	6.932	**221.94**[a]	98.952	30.32	195.531	133.20	83.870
	Winter	-1225.42	1227.878	**235.56**[a]	98.935	-131.98	354.530	**197.39**[a]	83.500
Winter	Autumn	-1547.44	1307.116	**-478.24**[a]	113.428	**-8779.96**[a]	2305.219	**-3316.20**[a]	574.609
	Spring	1219.63	1227.866	**-13.62**[a]	1.932	162.29	303.086	**-64.18**[a]	7.985
	Summer	1225.42	1227.878	**-235.56**[a]	98.935	131.98	354.530	**-197.39**[a]	83.500

[a] The mean difference is significant at the .05 level.

The overall Wald Chi-square is significant for all models at the .01 level.

IV. CONCLUSION

This paper investigated the effects of the seasons, and mobility trends on the number of COVID-19 cases for the period February-November 2020. Data of four European countries were used in this research: Austria, Czech Republic, Greece, and Italy. An NBR model with log link was developed for each country. The results showed that mobility and season parameters are statistically significant predictors of the COVID-19 registered cases in all the four countries. Considering the seasons, in all the four countries the number of COVID-19 cases increased in spring, summer, and autumn compared to the winter. In particular, the number of COVID-19 cases was lower in spring than in summer, compared to the winter, but also lower in summer than in autumn. Finally, in autumn, the number of cases was higher than in summer and spring, compared to the winter. Considering the effects of different types of mobility, the results revealed that an increase in grocery and pharmacy mobility trends increased the number of COVID-19 cases in three out of four countries.

The interaction relationships discovered statistically significant interaction effects between seasons and mobility in terms of the number of COVID-19 cases. It was found that in spring, summer, and autumn the number of COVID-19 cases increased with positive trends of transit stations mobility, compared to the winter. Hence, with more mobility the number of COVID-19 cases increased. Grocery and pharmacy mobility trends were found to interact with spring and summer by decreasing the number of COVID-19 cases, compared to the winter. This research represents the first attempt to analyse the cross interaction effects between seasons and mobility trend with COVID-19 number of cases. Still, more aspects should be explored and will be addressed in a future extension of this work. In particular, weather conditions were not accounted in the model, which could impact on the people mobility. Also, mobility restrictions or the behavior of the virus on different temperatures and in different weather conditions were not taken into account in the analysis. In the future, the proposed analysis will be extended including the other factors for a depth investigation.

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REFERENCES

[1] "COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU)". ArcGIS. Johns Hopkins University. Retrieved 7 December 2020.

[2] M.U. Kraemer et al., "The effect of human mobility and control measures on the COVID-19 epidemic in China," Science, vol. 368(6490), pp. 493-497, 2020.

[3] H.S. Badr, H. Du, M. Marshall, E. Dong, M.M. Squire, and L. M. Gardner, "Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study," The Lancet Infectious Diseases, vol. 20(11), pp. 1247-1254, 2020.

[4] T.H. Tran, S.N. Sasikumar, A. Hennessy, A. O'Loughlin, and L. Morgan, "Associations between restrictions on public mobility and slowing of new COVID - 19 case rates in three countries," The Medical Journal of Australia, vol. 213(10), pp. 471, 2020.

[5] I. Sirkeci and M. M. Yucesahin, “Coronavirus and Migration: Analysis of Human Mobility and the Spread of Covid-19,” Migration Letters, vol. 17, no. 2, pp. 379–398, Apr. 2020.

[6] S. Bönisch et al., “Effects of Coronavirus Disease (COVID-19) Related Contact Restrictions in Germany, March to May 2020, on the Mobility and Relation to Infection Patterns,” Frontiers in Public Health, vol. 8, Oct. 2020.

[7] A. Roy and B. Kar, “Characterizing the spread of COVID-19 from human mobility patterns and SocioDemographic indicators,” Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Advances in Resilient and Intelligent Cities, Nov. 2020.

[8] S. Chang et al., “Mobility network models of COVID-19 explain inequities and inform reopening,” Nature, pp. 1–8, Nov. 2020, doi: 10.1038/s41586-020-2923-3.

[9] A. Carteni, L. D. Francesco, M. Martino, “How mobility habits influenced the spread of the COVID-19 pandemic: Results from the Italian case study,” Science of The Total Environment, vol. 741, p. 140489, Nov. 2020, doi: 10.1016/j.scitotenv.2020.140489.

[10] Google LLC "Google COVID-19 Community Mobility Reports". https://www.google.com/covid19/mobility/ Accessed: Nov 17, 2020.

[11] Our World in Data, https://ourworldindata.org/coronavirus-data. Accessed: Nov 20, 2020.

[12] N. T. Longford, "A fast scoring algorithm for maximum likelihood estimation in unbalanced mixed models with nested random effects," Biometrika, vol 74 (4), pp. 817–827, 1987, doi:10.1093/biomet/74.4.817

[13] A. Schworer, and P. Hovey, "Newton-Raphson Versus Fisher Scoring Algorithms in Calculating Maximum Likelihood Estimates," Undergraduate Mathematics Day, Electronic Proceedings. Paper 1, 2004.

[14] H. Akaike, "A new look at the statistical model identification," IEEE transactions on automatic control, vol. 19(6), pp. 716-723, 1974.

[15] M. Stone, "Comments on model selection criteria of Akaike and Schwarz," Journal of the Royal Statistical Society. Series B (Methodological), pp. 276-278, 1979.

[16] K.P. Murphy, Machine Learning – A Probabilitstic Perspective.The MIT Press, Cambridge, Massachusetts, London, England. 2012.

[17] R. F. Engle, "Wald, likelihood ration, and Lagrange multiplier tests in econometrics", Handbook of Econometrics, Vol 2, pp. 775-826, 1984.