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Modelling the relationship between covid-19 restrictive measures and mobility patterns across Europe using time-series analysis

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Since early 2020, strict restrictions on non-essential movements were imposed globally as countermeasures to the rapid spread of COVID-19. The various containment and closures strategies, taken by the majority of countries, have directly affected travel behavior. This paper aims to investigate and model the relationship between covid-19 restrictive measures and mobility patterns across Europe using time-series analysis. Driving and walking data, as well as confinement policies were collected from February 2020 to February 2021 for twenty-five European countries and were implemented into Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors (SARIMAX) time-series models. Results reveal a significant number of models in order to estimate mobility during pandemic almost in every country of the study. School closing was found to be the most important exogenous factor for describing driving or walking, while "Stay at home" orders had not a significant effect on the evolution of people movements. In addition, countries which suffered the most due to the pandemic indicated a strong correlation with the restrictive measures. No time-series models were found to describe the countries which implemented weak confinement policies.

Keywords: *COVID-19 pandemic, driving, restrictive measures, SARIMAX time-series models, travel behavior, walking..*

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1. Introduction

COVID-19, a contagious disease caused by a new coronavirus called SARS-CoV-2, was initially identified in Wuhan, China in December 2019. Due to the rapid spread around the globe, a pandemic was declared on March 11, 2020 (WHO, 2020). As of October 2021, confirmed cases of the disease exceed 236 million, including 4.8 million casualties (WHO, 2021).

As countermeasures to the high transmissibility of COVID-19, "social distancing" and "lockdown" measures were imposed globally, in order to diminish the infections and thus the emergency hospitalizations. The restrictive measures mainly concerned the closure of schools and workplaces, limits on gatherings, orders to "stay at home" and restrictions on internal movements and on international travel. (Hale et al., 2021) Moreover, distance learning, teleworking and digital adaptation of daily activities were promoted.

The aforementioned countermeasures, as well as the fear of exposure to the virus, had a direct impact on travel behavior. Public transport users and overall mobility have been radically reduced. For instance, in European Union driving was reduced up to 89%, while the use of public transportation fell up to 93% the first months of the pandemic (Apple, 2021; Google LLC, 2021). At the same time, in many European cities an increased interest in cycling, shared bicycles and walking was observed (Bucsksy, 2020; Molloy et al., 2020). As a result, the mobility trends have changed leading to new unknown patterns.

Taking all the above into account, the aim of the paper is to investigate and model the relationship between covid-19 restrictive measures and mobility patterns across Europe. More specifically driving and walking data were collected for twenty-five state members of the European Union using the Apple Mobility Report, which acts as a surrogate for driving and walking volumes during the time of the pandemic. The European Union was selected as a study case, since the outbreak of the confirmed cases in 2020 has followed the same "wave" pattern, with the first "wave" during spring of 2020 and the second "wave" in the late summer and autumn (Our World in Data, 2021). Moreover, the majority of the chosen countries has followed similar strategies to control the spread of the virus. To fulfil the aim of the paper, seasonal time series models were implemented, in order to compare mobility trends during "lockdowns" and the summer easing of restrictions, as well as the effect of different national strategies on travel behavior.

The paper is structured as follows: after the introduction to the problem, a brief literature review on travel behavior regarding the pandemic of COVID-19 or previous pandemics is taking place. This is followed by a description of the methodological approach, including the theoretical background of time-series forecasting analysis. Then, the data analysis method utilized and the results of the statistical analysis performed are presented. Finally, conclusions on the impact of COVID-19 pandemic on travel behavior in European Union are provided and a discussion on how researchers should take advantage of the analysis is highlighted.

2. Literature review

A scientific literature review was conducted in the databases ScienceDirect, Scopus and Google Scholar, in order to link driving behavior, mobility and transportation with the European countermeasures during the COVID-19 pandemic. The key terms entered into the databases were: "COVID-19" or "Corona Virus" or "SARS Cov2" and "traffic" or "travel" or "behavior" or "mobility" or "road" or "safety" or "countermeasures" or "EU" or "lockdown". The most relevant studies to the investigating topic were decided to be included in this review and are described below.

The movement restrictions implemented by the majority of countries worldwide have directly affected travel behavior. Beria et al. (2021) revealed a dramatic drop, up to 80%, in internal movements during the first lockdown week in Italy and the disappearance of weekend trips until May 2020. In the same context, in March 2020, first in Italy and then in other European countries mobility was reduced sharply, a fact that can be explained up to 90% due to the confinement measures (Santamaria et al., 2020). The impact of preventive measures on traffic behavior was also investigated by Muley et al. (2021) in the State of Qatar and traffic volumes were found to be massively decreased the day after the implementation of each measure (e.g., closure of educational institutions, parks, all commercial stores and public transport). Although further restrictions regarding international travel were executed, the aforementioned volume fall was halted as the Holy Month of Ramadan was approaching. Similarly, traffic decline in Florida corresponded to school, bar and restaurant closures (Parr et al., 2020).

During the first weeks of lockdown measures, driving volumes were diminished by 75% and 50% in Greece and in Saudi Arabia, leading to a 6-11% average speed increase (Katrakazas et al., 2020). Distance learning and teleworking resulted to a 77% movement decline during rushing hours in France (Pullano et. al, 2020). In Budapest, mobility was reduced by 77% and less traffic jams were observed accompanied by the limited use of route planning applications (Bucsksy, 2020). The lockdown policy in Spain caused shorter trips and an overall decreased activity by 67% in the city of Santander (Aloi et al., 2020), as well as reduced mobility by 63% and less traffic accidents by 74% in Tarragona province (Saladié et al., 2020). In contrast to the above, Japan did not impose any mandatory curfew, nor penalties, but only encouraged citizens to limit their public activities, resulting to a 45% reduction of trips in Tokyo and a 27% reduction in Osaka (Hara et. al, 2020). Analyzing data from toll gates on expressways, Lee et al. (2021) observed sharp drop in traffic inflow volumes when the first and the second "wave" occurred, despite the non-compulsory orders to stay at home and practice social distancing in Korea.

A study in UK provided evidence of the connection of human mobility with government measures and COVID-19 related deaths. The day after the general lockdown, driving, walking and transit had a massive reduction by 60%, 60% and 80%, respectively, followed by a lower number of deaths 18 days later (Hadjidemetriou et al., 2020). Habib et al. (2021) analyzed daily mobility data through non-linear modeling, indicating the negative linkage between COVID-19 cases and travel behavior and vice versa. COVID-19 has significantly reduced driving, walking and transit volumes, which in turn mitigate the high transmissibility of the virus. Another research investigated the effect of lockdown orders in ten countries and reported that early responses and actions, resulted to relatively higher mobility volumes (up to 40% of pre-COVID volumes) and lower mortality rates, proving that pandemic affected all countries' mobility, even those with loose imposed measures or lower cases and casualties (Gargoum and Gargoum, 2021). Using time-series modelling, Truong and Truong (2021) examined the relationship between daily trips by distance and COVID-19 infections and deaths in USA and revealed that travel behavior appeared to change dynamically according to risk awareness of the disease.

Travel behavior and especially transit trips can be influenced by the fear of exposure, as Kim et al., (2017) demonstrated during the MERS outbreak in South Korea in 2017. Factors that determined mode choice in pre-coronavirus era, such as travel time saving, comfort and cost, became less priority during the pandemic (Abdullah et al., 2020). During the first "wave" of COVID-19 in China, commuters' choice of mode of transport was dictated by the possibility of getting infected (Tan and Ma, 2020). Many surveys indicated an important shift from usage of public modes of transport to private ones use (Abdullah et al., 2021; Shakibaei et al., 2021; Shamshiripour et al., 2020). These results are in line with the data analysis findings of Aloi et al. (2020) and Bucsksy (2020), which showed a 90% drop of public transport. Another survey found a 50% decline in trips by car during "Stay at home" orders in Australia, but raised questions about and the increased car use and the future congestions after the measure easing (Beck and Hensher, 2020).

With respect to walking volumes, a similar reduction was identified, although to a lesser degree than the massive reduction of transit trips. Abdullah et al. (2021) noticed an important shift from motorized modes to walking and cycling. Walking was preferred for short distances as a safer and healthier mode of transport (Tan and Ma, 2020; Muley et al., 2020). Aloi et al. (2020) observed a significant reduction of pedestrian flows during the morning rush hour, while Jenelius and Cebecauer (2020) found pedestrian mobility stable in the outer city and up to 60% declined in the inner city. In the Netherlands, walking had the smallest decrease (14%) of overall mobility and the average distance (83%) of walking trips was increased (de Haas et al., 2020). A survey conducted in Germany revealed an important shift from regular transport use to walking, cycling and gradually driving, resulting to an increased proportion of walking trips compared to pre-pandemic era (Anke et al., 2021).

As it can be understood from the state-of-the-art literature, the majority of the papers investigating the effect of COVID-19 on travel behavior perform before/after descriptive analyses and only few of them explore statistical models, taking into account time patterns. In addition, a gap in literature exists regarding the impact of the current pandemic across various countries. The present paper will attempt to conduct an exploratory and confirmatory study in European countries by utilizing time-series modelling for driving and walking data. The time series analysis was chosen in order to quantify the daily effect of COVID-19 restrictions on travel behavior in each country and compare the results with the other countries of the study.

3. Methodology

Time-series analysis has been repeatedly used in a wide range of transportation studies, in order to predict future conditions from observed past data (Lavrenz et al., 2018). Especially during COVID-19 crisis, many researchers have implemented seasonal time-series models to analyze the daily effect of the pandemic on travel behavior and road safety (Adreana et al., 2021; Sekadakis et al., 2021; Katrakazas et al., 2021; Truong and Truong, 2021).

Regarding the present analysis, the available time-series were split into several components (i.e. trend-cycle, seasonal and residual) to detect the underlying patterns. This procedure exhibits the variety of time-series patterns and it is crucial for the methodology selection (Hyndman and Athanasopoulos, 2018). In Figure 1, a definite weekly seasonality is observed. SARIMAX models are a suitable methodology in order to handle the presented seasonality and the profound relationship between travel behavior and the national countermeasures. Driving and walking percentage changes represent the endogenous variables, while the implemented restrictive measures (i.e., “Stay at home” policy, School closing and International travel controls) are the exogenous variables.

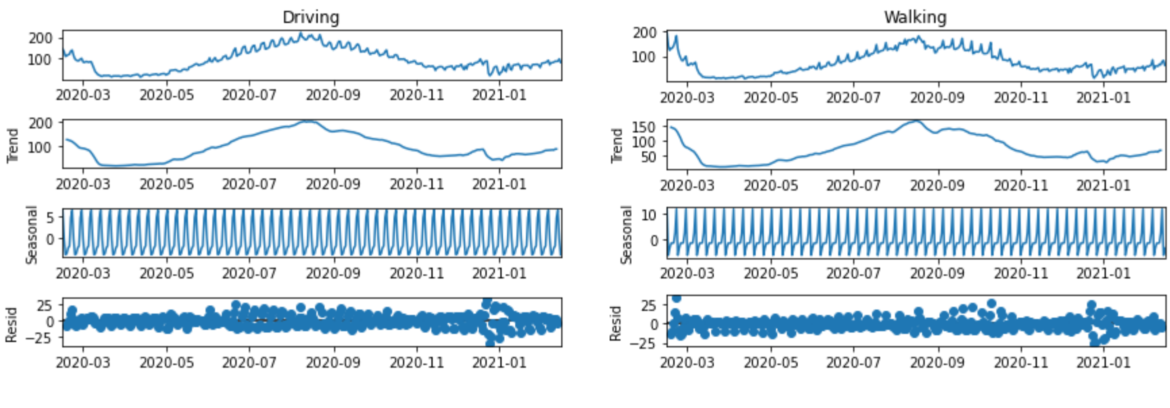


Figure 1. Seasonal decomposition of driving and walking percentage changes in Italy during COVID-19 pandemic

Box and Jenkins (1976) first introduced one of the most commonly used methodologies for time-series analysis, known as AutoRegressive Integrated Moving Average (ARIMA) models. ARIMA models support both autoregressive and moving average elements and handle time-series data with a trend, but do not capture adequately any seasonal components. Taking into account the importance of seasonality for the present analysis, Seasonal AutoRegressive Integrated Moving Average (SARIMA) is used to overstep this problem and provide more targeted models by introducing autoregressive and moving average polynomials that identify seasonal lags. SARIMA is generally denoted as:

$$SARIMA\ (p, d, q)\ (P, D, Q, s) \tag{1}$$

A further extension of the aforementioned model is Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors (SARIMAX) model, which incorporates exogenous time-series that affect the observed data. According to Box and Jenkins (1976), the construction of an ARIMA model consists of a specific process and includes model identification, parameter estimation and statistical model checking. The following steps are followed:

- Time-series decomposition
- Test for non-stationarity
- Model parameter search
- SARIMAX modelling
- Evaluation tests

Regarding the model identification, the decomposition of time-series is first required (Figure 1) to determine the implemented seasonal lag *s* of the model by the detected seasonality. Then, the Augmented Dickey-Fuller test (Dickey & Fuller, 1979) is used, in order to check if the utilized time-series are stationary. A time-series that shows seasonality is not stationary and can be transformed through first differencing (i.e. the difference between two consecutive observations).

The parameters of the SARIMAX model, as mentioned in equation (1), are estimated through an algorithmic search, which is executed automatically in Python programming environment utilizing pmdarima package (Hyndman and Khandakar, 2008). This algorithmic search is based on the Akaike information criterion (AIC), the Bayesian information criterion (BIC) and the Hanna-Quinn information criterion (HQIC). AIC method identifies the best forecasting model of the given data through a log-likelihood function, but also considers the number of estimated parameters within the model (Akaike, 1974). In the same way, BIC and HQIC are model selection criterions based on likelihood function, with a stricter penalty term for the number of parameters (Schwarz, 1978). The most optimal parameters depend on the lowest AIC, BIC and HQIC scores.

Before applying the best fitted models, the known data should be split into a training representative dataset on which to fit the models and a testing dataset to evaluate the results. Then, the model forecasts are compared with the remaining observed data. Due to various mobility patterns and the different national strategies against the pandemic, four cases were created to find statistically significant models for each country. The specific dates of training, testing and forecasting sets are shown in Table 1. It should be noted that the starting date of training sets (16/02/2020) corresponds to an era before the main outburst of COVID-19. The case-control study approach, widely used to real-time crash prediction studies (Abdel-Aty et al, 2004; Yu and Abdel-Aty, 2014), was utilized in order to capture both pre-pandemic (control) and pandemic (case) times in the analysis.

Table 1. An overview of training, testing and forecasting sets

	Training set	Testing set	Forecasting set
Case 1	16/02/20 to 15/04/20 (beginning of 1st "wave")	16/04/20 to 15/06/20 (1st "wave)	16/06/20 to 15/02/21 (summer easing and 2nd "wave)
Case 2	16/02/20 to 15/06/20 (1st "wave")	16/06/20 to 31/08/20 (summer easing)	01/09/20 to 15/02/21 (2nd "wave")
Case 3	16/02/20 to 15/09/20 (1st "wave" and summer easing)	16/09/20 to 15/11/20 (beginning of 2nd "wave")	16/11/20 to 15/02/21 (2nd "wave")
Case 4	16/02/20 to 30/11/20 (1st "wave" and beginning of 2nd "wave")	01/12/20 to 15/01/21 (2nd "wave")	16/01/2021 to 15/02/21 (end of 2nd "wave")

Following the above procedure, the forecasts of the SARIMAX models are evaluated using popular accuracy metrics such as:

- Mean Absolute Percentage Error (MAPE), which is the average of the percentage errors:

$$MAPE = \frac{1}{n}\sum \frac{|e_t|}{d_t} \quad (2)$$

- Mean Absolute Error (MAE), which is the mean of the absolute error:

$$MAE = \frac{1}{n}\sum |e_t| \quad (3)$$

- Root Mean Squared Error (RMSE), which is the square root of the average squared error:

$$RMSE = \sqrt{\frac{1}{n}\sum {e_t}^2} \quad (4)$$

- Mean Squared Error (MSE), which is the average squared error:

$$MSE = \frac{1}{n}\sum {e_t}^2 \quad (5)$$

4. Data description and pre-processing

For this research, data were extracted from the mobility trend report of Apple (Apple, 2021), in which route requests are measured and divided into driving, walking and public transport use. The data are expressed as daily percentage changes from the 100% baseline volume on January 13th, 2020. More specifically, driving and walking data were collected for twenty-five countries, namely Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden and correspond to a time span from

15/02/2020 to 15/02/2021. Figure 2 and Figure 3 depict the 7-day moving average percentage change of driving and walking sessions of Apple users on the aforementioned time span. Table 2 and Table 3 provide some descriptive statistics (i.e., mean, standard deviation, maximum, minimum value and sample size) for driving and walking percentage changes, respectively.

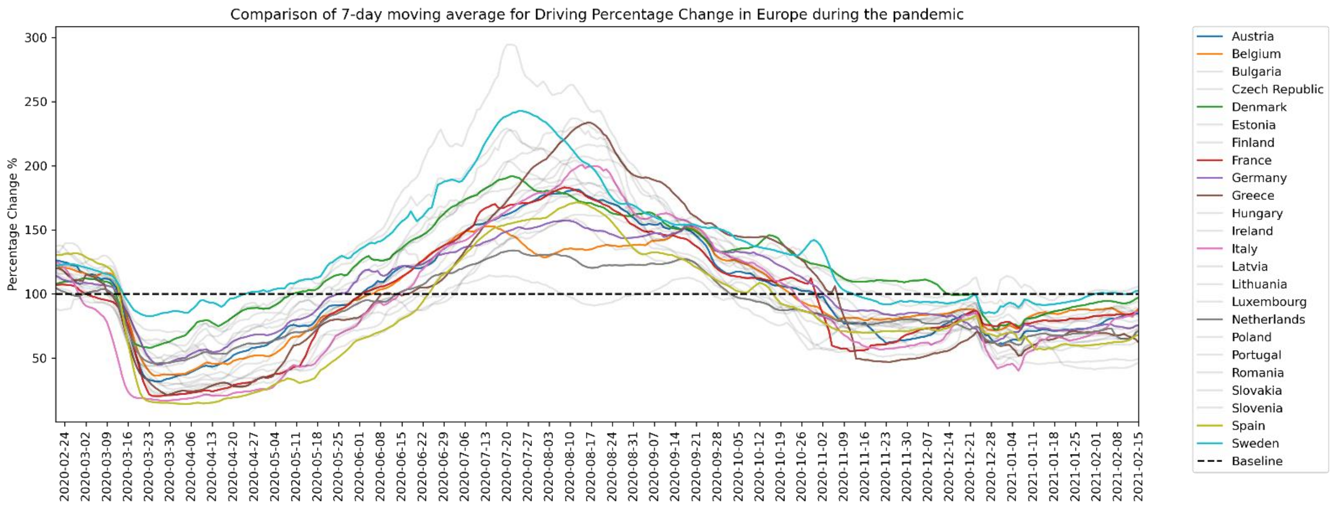


Figure 2. Comparison of 7-day moving average for driving percentage change in Europe during the pandemic (Source: Apple)

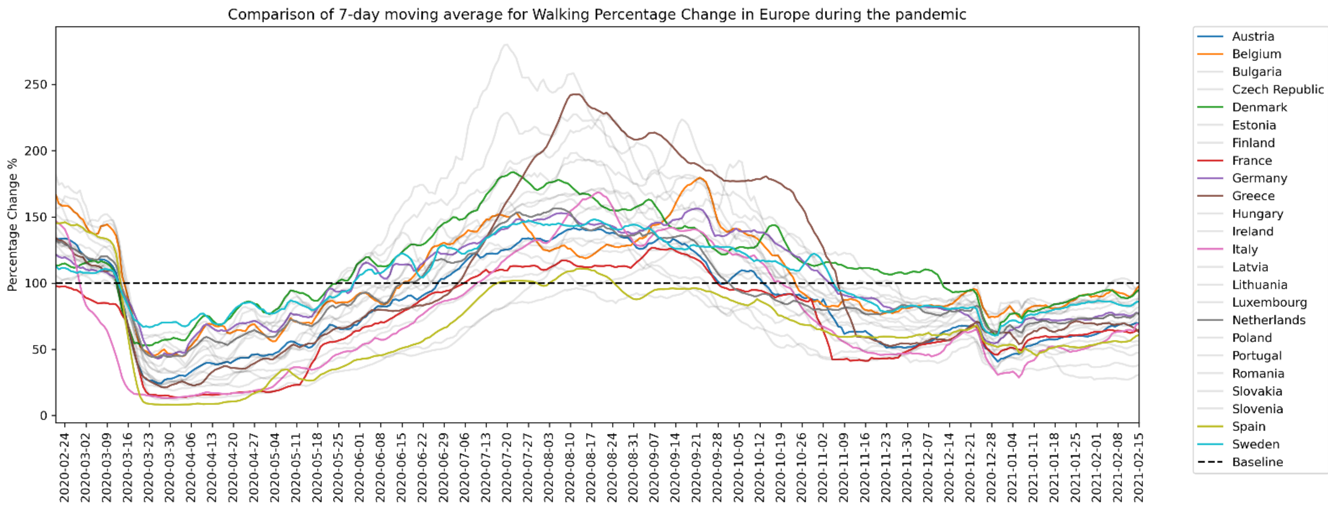


Figure 3. Comparison of 7-day moving average for walking percentage change in Europe during the pandemic (Source: Apple)

Table 2. Descriptive statistics for driving percentage changes from 15/02/20 to 15/01/21 (Sample size: 367)

Country	Mean	Standard deviation	Minimum value	Maximum value
Austria	101.90	41.61	24.83	194.72
Belgium	99.35	33.06	29.76	169.29
Bulgaria	103.30	48.89	25.56	224.46
Croatia	147.96	138.34	20.51	670.50
Czech Republic	111.04	42.04	31.86	206.84
Denmark	119.92	35.86	50.61	203.67
Estonia	137.28	62.56	52.04	340.21
Finland	129.02	41.45	54.91	242.43
France	97.38	45.49	15.33	196.95
Germany	103.19	33.36	37.90	170.31
Greece	102.02	58.67	18.59	241.14
Hungary	104.96	37.42	35.85	196.46
Ireland	82.57	39.05	19.52	166.38
Italy	93.24	53.06	12.66	222.86
Latvia	115.43	52.42	46.42	267.09
Lithuania	108.60	48.61	27.11	236.39
Luxembourg	77.28	25.83	18.20	137.89
Netherlands	89.41	26.12	38.99	147.61
Poland	103.85	42.84	19.78	205.90
Portugal	92.60	53.35	16.78	231.07
Romania	91.53	37.26	18.78	176.19
Slovakia	99.20	39.94	28.87	191.93
Slovenia	102.49	59.74	24.74	304.21
Spain	86.50	44.72	10.93	175.04
Sweden	131.56	44.47	47.76	252.55

Table 3. Descriptive statistics for walking percentage changes from 15/02/20 to 15/02/21 (Sample size: 367)

Country	Mean	Standard deviation	Minimum value	Maximum value
Austria	83.73	35.91	18.54	166.41
Belgium	103.66	35.47	34.50	235.37
Bulgaria	106.14	48.61	19.15	207.45
Croatia	174.94	184.80	17.06	888.44
Czech Republic	74.35	36.54	16.13	195.40
Denmark	113.44	35.68	36.80	196.81
Estonia	132.00	62.45	36.01	316.12
Finland	104.62	29.91	37.00	177.78
France	71.20	34.50	10.44	137.30
Germany	101.99	33.60	33.95	194.18
Greece	105.66	64.05	18.00	254.21
Hungary	73.71	35.14	18.20	213.12
Ireland	62.69	33.11	14.95	196.24
Italy	74.81	45.37	10.97	194.34
Latvia	99.19	48.29	32.43	220.25
Lithuania	118.32	59.35	30.03	275.76
Luxembourg	87.98	28.73	24.14	147.40
Netherlands	94.42	32.73	33.84	173.30
Poland	93.40	45.16	15.90	186.57
Portugal	69.31	47.09	10.21	196.41
Romania	88.44	36.49	13.91	151.22
Slovakia	101.73	40.90	24.62	194.01
Slovenia	113.65	55.25	28.86	262.90
Spain	66.39	35.50	5.82	192.60
Sweden	102.73	27.25	32.87	158.70

With regards to confinement measures, the study has used data from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2021), an online database that collects information on governments' policies against the spread of the disease and classifies them into the following eight indicators: C1 (School and universities closure), C2 (Workplace closure), C3 (Cancelling of public events), C4 (Limits on gatherings), C5 (Closing of public transport), C6 (Orders to "stay at home"), C7 (Restrictions on internal movements between cities and regions) and C8 (Restrictions on international travel).

Cancelling of public events was the first applied countermeasure for the majority of European countries and there was no easing till 2021. School and universities closure followed and had an immediate impact on the youth population mobility and consequently on the family outdoor movements. As ITF Report (2021) showed, a major drop in road fatalities in young people aged 0-17 years occurred due to school closing. The workplace closure and the closing of public transport were implemented only by few countries, while limits on gatherings and on internal movements were not strictly executed in many cases. Orders to "stay at home", also known as lockdown measures, were probably the most restrictive policy and was widely implemented in European Union. Orders to "stay at home" limited additionally public events, crowded gatherings, public transport use, commuting to or from workplaces and internal movements. Hence, C1 was strongly correlated with C2, C3, C4, C5 and C7. Restrictions on international travel were imposed in all countries, especially those that did not implement other measures, to prevent the transmission of the virus from other countries. Easing of travel bans was spotted in many European countries during the summer of 2020, indicating the link of this indicator with tourism, a factor with major effects in mobility trends.

Taking the above into consideration, C1, C6 and C8 were selected as the most representative factors. These indicators are recorded on a scale from 0 to 2, 3 or 4 in relation to the strictness of the applied measures and are accompanied by a binary flag to denote the geographic scope (targeted or general). For the current analysis, the indicators were transformed to a binary quantity, denoting no measure application (e.g. as before COVID-19) to 0 and recommended or required measures (e.g. night curfew or universal lockdown) to 1, as shown in Table 4. In addition, the flags are not utilized, but they could be used in a further analysis of the sub-national regions. Figure 4 provides an overview of the timeline of COVID-19 response measures taken by the European governments along with COVID-19 Cases.

Table 4. Indicators for containment and closure policies

Indicators	Description	Coding
C1	Schools and universities closure	0: no measure 1: recommend/require closing of some/all levels
C6	"Stay at home" order	0: no measure 1: recommend/require not leaving house with minimal exceptions
C8	Restrictions on international travel	0: no restrictions 1: quarantine/ ban arrival from some/all regions

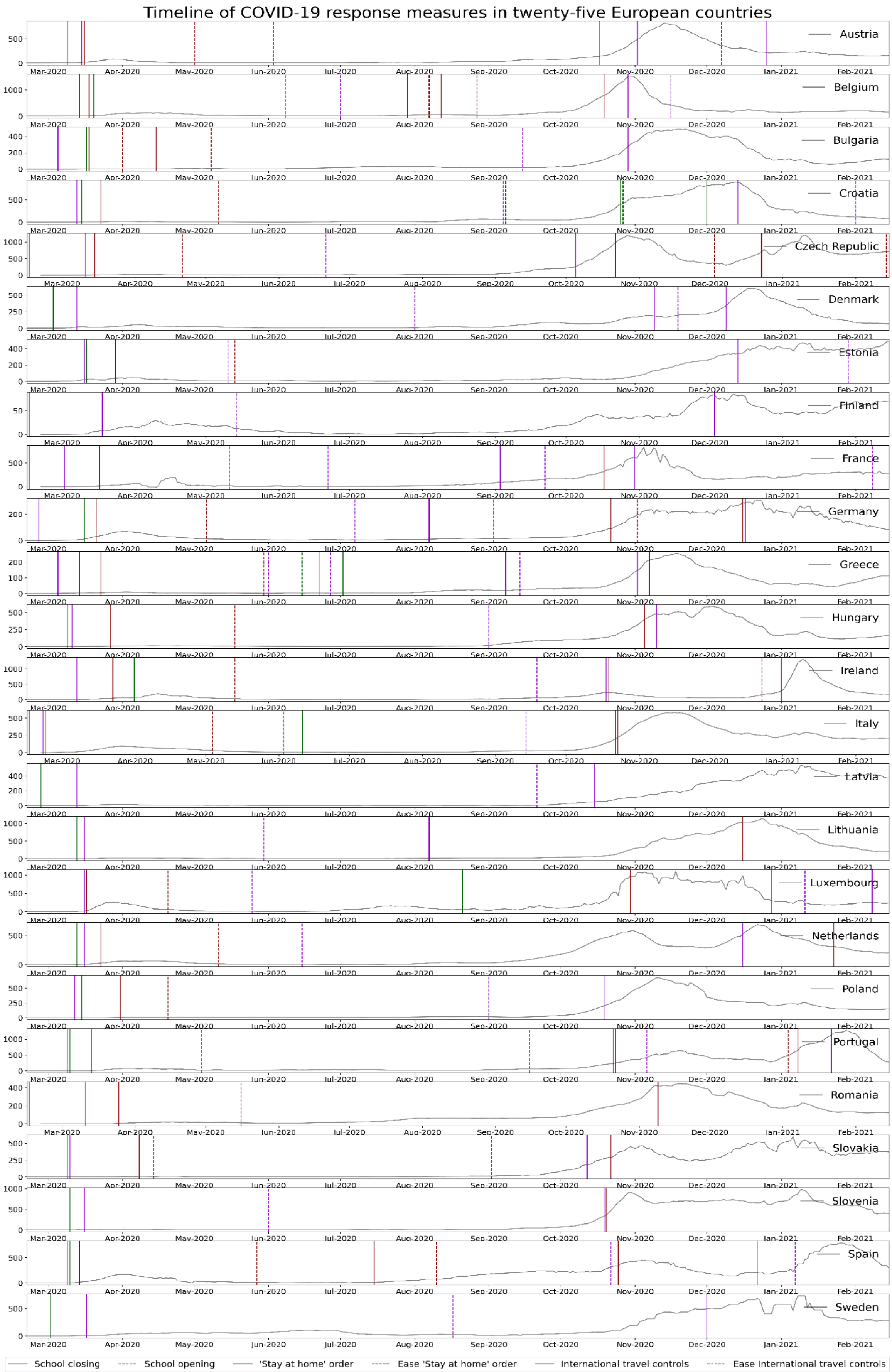


Figure 4. Dates of lockdown measures in twenty-five European countries

5. Results

SARIMAX modelling was followed for each country regarding driving and walking data in relation to three exogenous variables. Through the decomposition of the available time-series, three components (i.e. trend, seasonality and residuals) were examined. A weekly seasonality was detected in each decomposition and implemented in the models (i.e., s=7). Moreover, the ADF test was performed and revealed the non-stationarity of all the original time-series. In order to eliminate trend and the seasonality, first differencing was utilized and time-series were transformed to stationary, as shown in Table 5.

Table 5. ADF Test results on differenced time-series

Augmented Dickey-Fuller Test:	
ADF test statistic	-4.0169
p-value	0.0013
# lags used	13.0000
# observations	352.0000
Critical value (1%)	-3.4491
Critical value (5%)	-2.8698
Critical value (10%)	-2.5712
Strong evidence against the null hypothesis	
Reject the null hypothesis	
Data has no unit root and is stationary	

The most important step was to detect the best fitted models. Four cases, as shown in Table 1, were executed to find statistically significant models with minimized forecast errors. Figure 5 presents an overview example of the observed time-series, the train, the test and the forecast set of SARIMAX driving model in Ireland. First, endogenous train and test set were implemented into the model selection algorithm, in order to estimate the parameters (p, d, q) (P, D, Q). Then, these parameters were applied into a new model with the train set of both endogenous and exogenous variables and the obtained SARIMAX models were tested within the specific case time span. If only the p-values were found to be less or equal to 0.05, the candidate models were used for further forecasts, which were validated utilizing the evaluation metrics of equations (2), (3), (4) and (5). This procedure, as depicted in Figure 6, was executed for driving and walking data, separately for the three exogenous variables for the twenty–five countries for all the four cases. Visual inspection and MAPE, MAE, RMSE, MSE metrics were utilized to exclude the models with major errors. The optimal SARIMAX models are presented in the Table 6 and in the Figures 7-12.

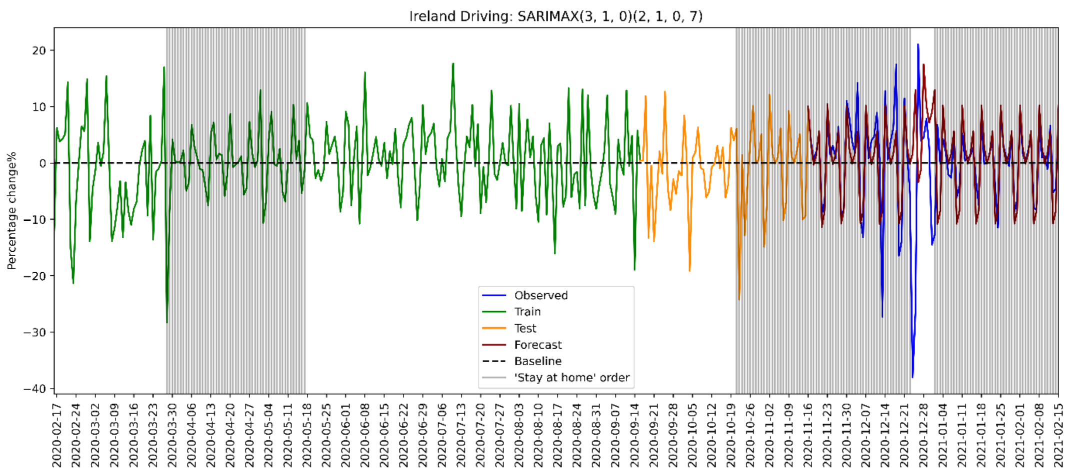


Figure 5. SARIMAX model of driving in relation to "Stay at home" orders in Ireland

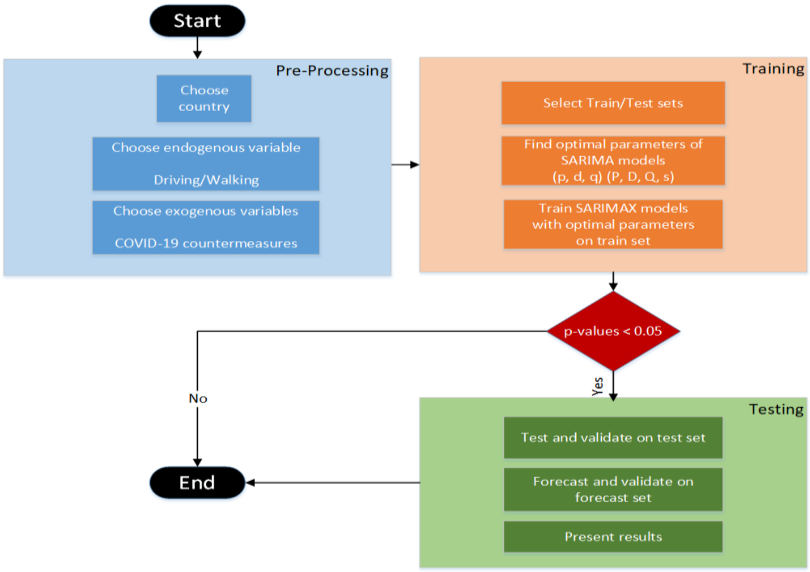


Figure 6. Flow chart

Table 6. Summary of optimal SARIMAX models

N.	Country	SARIMAX	Case	Endogenous variable	Exogenous variable	MAPE	MAE	RMSE	MSE	Figure
1	Austria	(3,1,0)(1,1,1,7)	4	Driving	School closing	3.16	4.48	5.93	35.22	7.a
2	Belgium	(3,1,0)(2,1,0,7)	3	Driving	School closing	8.76	5.82	8.20	67.22	7.b
3	Czech Republic	(2,1,1)(1,1,0,7)	2	Driving	School closing	3.17	12.85	15.60	243.44	7.c
4	Denmark	(3,1,0)(2,1,0,7)	1	Driving	School closing	2.90	8.92	11.39	129.77	7.d
5	France	(3,1,0)(0,1,1,7)	4	Driving	School closing	2.54	9.75	11.60	134.58	7.e
6	Greece	(2,1,2)(1,1,1,7)	4	Driving	School closing	10.60	4.10	5.33	28.42	7.f
7	Hungary	(0,1,2)(0,1,1,7)	2	Driving	School closing	1.43	7.74	10.90	119.11	7.g
8	Netherlands	(0,1,1)(0,1,2,7)	2	Driving	School closing	0.68	3.92	6.38	40.71	7.h
9	Poland	(3,1,1)(0,1,1,7)	1	Driving	School closing	3.02	18.88	22.38	500.67	7.i
10	Spain	(3,1,0)(2,1,0,7)	3	Driving	School closing	4.34	6.08	7.61	57.90	7.j
11	Austria	(3,1,0)(1,1,1,7)	4	Walking	School closing	4.91	3.39	4.50	20.29	8.a
12	Czech Republic	(3,1,0)(1,1,1,7)	4	Walking	School closing	7.06	3.62	5.22	27.28	8.b
13	Denmark	(3,1,1)(0,1,1,7)	1	Walking	School closing	4.10	12.22	15.66	245.20	8.c
14	Hungary	(3,1,0)(0,1,2,7)	2	Walking	School closing	1.91	6.57	12.74	162.32	8.d
15	Italy	(3,1,0)(0,1,1,7)	4	Walking	School closing	4.71	7.96	12.19	148.52	8.e
16	Romania	(3,1,0)(2,1,0,7)	3	Walking	School closing	10.50	8.33	10.58	111.99	8.f
17	Slovakia	(3,1,0)(0,1,2,7)	4	Walking	School closing	1.52	6.35	7.37	54.28	8.g
18	Spain	(3,1,0)(2,1,0,7)	3	Walking	School closing	1.78	16.08	17.87	319.39	8.h
19	France	(3,1,0)(2,1,0,7)	1	Driving	"Stay at home"	2.69	6.97	10.20	105.57	9.a
20	Greece	(3,1,0)(0,1,1,7)	4	Driving	"Stay at home"	17.17	7.23	9.16	83.87	9.b
21	Ireland	(3,1,0)(2,1,0,7)	3	Driving	"Stay at home"	2.91	4.58	8.21	67.36	9.c
22	Slovakia	(0,1,1)(0,1,1,7)	2	Driving	"Stay at home"	3.11	9.99	14.50	210.44	9.d
23	Czech Republic	(3,1,0)(0,1,1,7)	3	Walking	"Stay at home"	3.63	5.21	6.97	48.58	10.a
24	Germany	(3,1,0)(2,1,0,7)	4	Walking	"Stay at home"	0.96	10.69	12.50	156.33	10.b
25	Greece	(3,1,0)(0,1,1,7)	4	Walking	"Stay at home"	2.63	8.58	10.83	117.37	10.c
26	Ireland	(3,1,0)(1,1,1,7)	4	Walking	"Stay at home"	9.03	2.88	3.69	13.64	10.d
27	Italy	(3,1,0)(0,1,1,7)	4	Walking	"Stay at home"	3.94	7.96	12.20	148.84	10.e
28	Netherlands	(0,1,1)(0,1,2,7)	2	Walking	"Stay at home"	0.82	6.85	9.20	84.79	10.f
29	Austria	(3,1,0)(1,1,1,7)	4	Driving	Travel controls	5.38	5.44	7.02	49.29	11.a
30	Belgium	(3,1,0)(2,1,0,7)	3	Driving	Travel controls	3.12	7.09	9.48	89.94	11.b
31	Hungary	(0,1,2)(0,1,1,7)	2	Driving	Travel controls	1.74	8.17	11.39	129.81	11.c
32	Italy	(0,1,2)(1,1,2,7)	2	Driving	Travel controls	1.48	12.57	17.45	304.39	11.d
34	Latvia	(3,1,1)(1,1,2,7)	2	Driving	Travel controls	4.83	9.63	12.66	160.24	11.e
33	Slovakia	(3,1,0)(0,1,2,7)	1	Driving	Travel controls	1.80	15.40	18.26	333.26	11.f
35	Croatia	(3,1,0)(2,1,0,7)	1	Walking	Travel controls	2.35	38.13	45.30	2052.62	12.a

N.	Country	SARIMAX	Case	Endogenous variable	Exogenous variable	MAPE	MAE	RMSE	MSE	Figure
36	Poland	(3,1,0)(2,1,0,7)	3	Walking	Travel controls	2.31	11.68	14.63	213.94	12.b
37	Portugal	(3,1,0)(1,1,1,7)	3	Walking	Travel controls	2.49	7.95	10.81	116.85	12.c
38	Slovakia	(1,1,2)(0,1,1,7)	2	Walking	Travel controls	5.80	12.81	16.82	283.00	12.d
39	Slovenia	(0,1,3)(0,1,1,7)	2	Walking	Travel controls	2.15	27.39	32.75	1072.86	12.e
40	Spain	(3,1,0)(2,1,0,7)	1	Walking	Travel controls	3.03	11.63	13.30	177.02	12.f

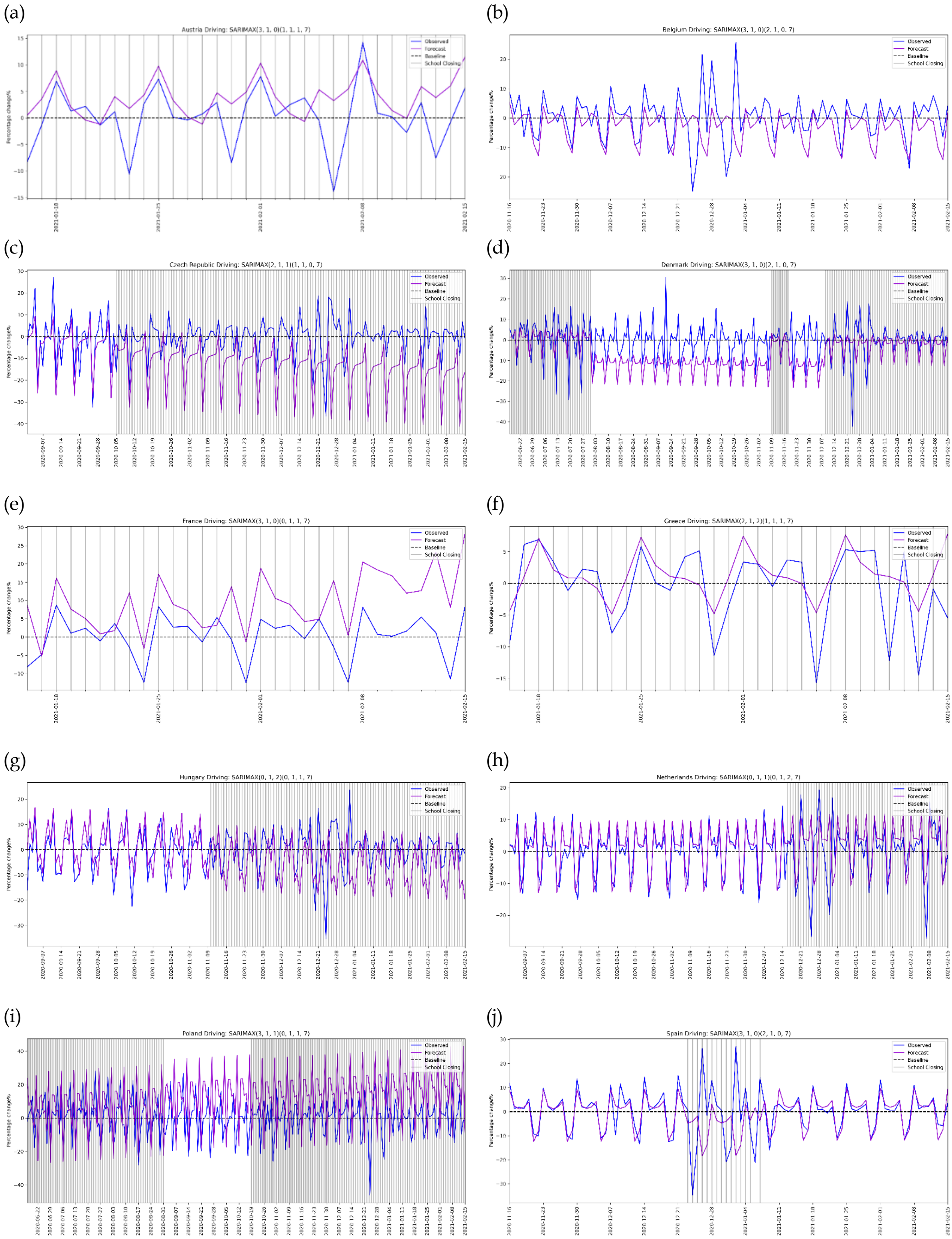


*Figure 7. SARIMAX forecasts for driving in relation to school closing (**a:** Austria, **b:** Belgium, **c:** Czech Republic, **d:** Denmark, e: France, **f:** Greece, **g:** Hungary, **h:** Netherlands, **i:** Poland, **j:** Spain)*

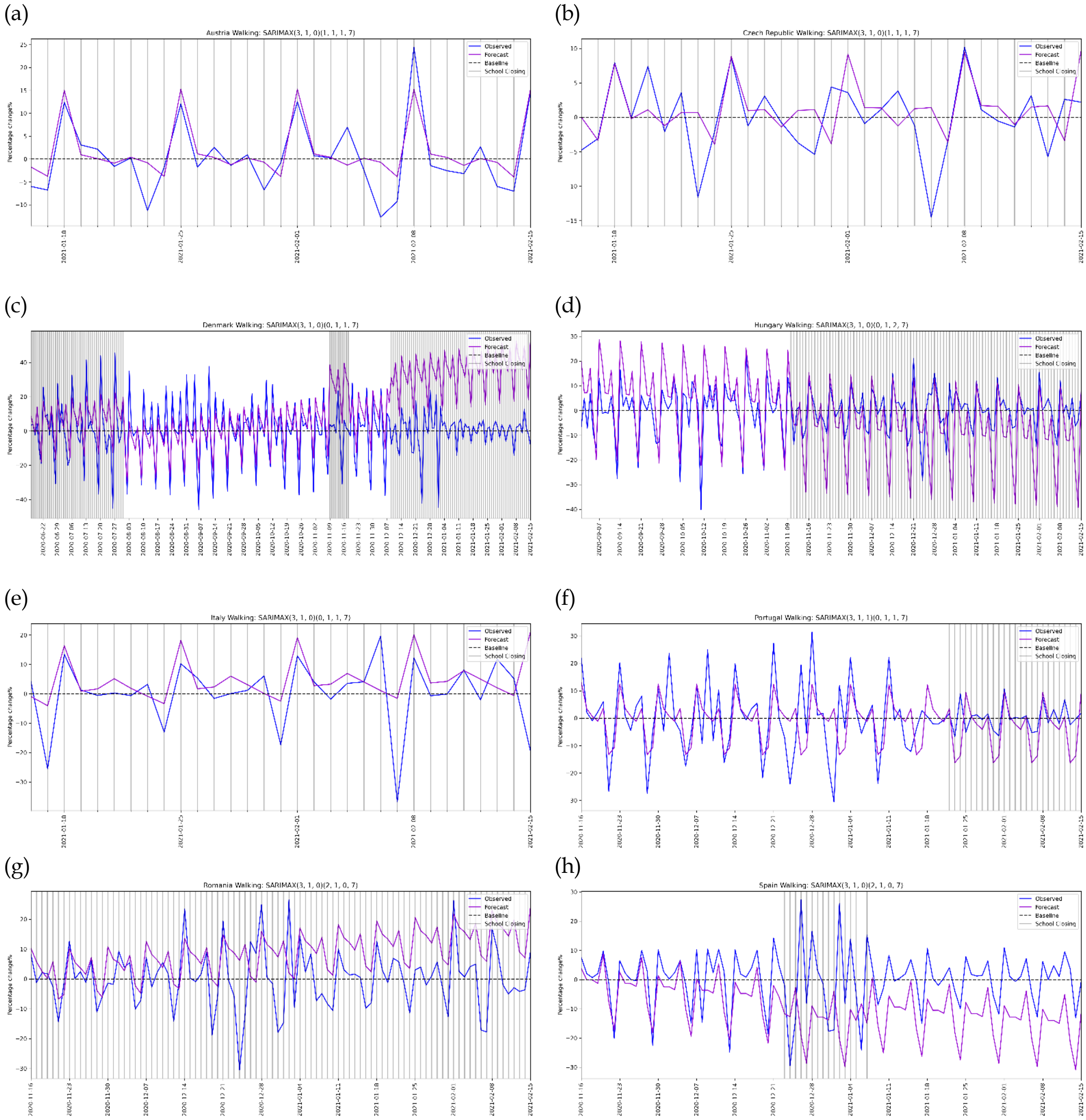
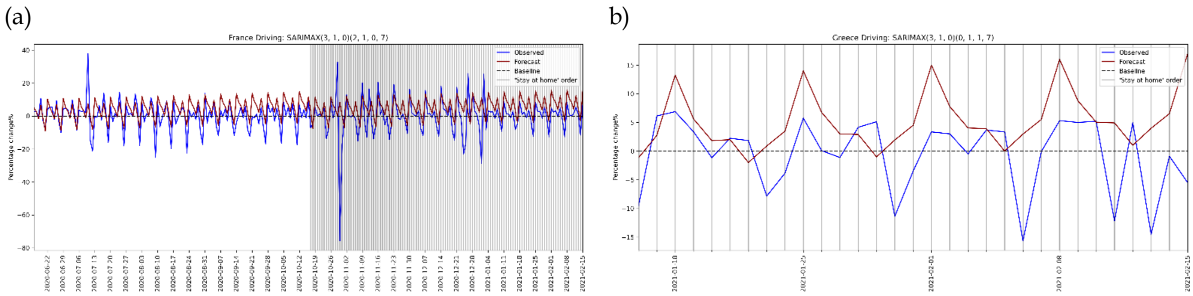
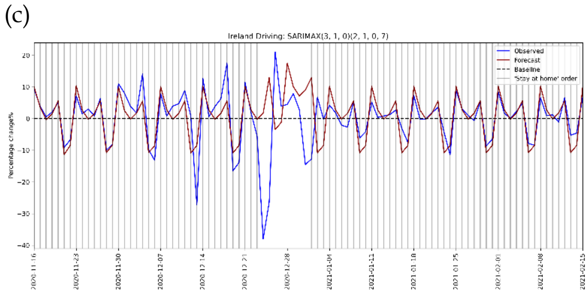


Figure 8. SARIMAX forecasts for walking in relation to school closing (a: Austria, b: Czech Republic, c: Denmark, d: Hungary, e: Italy, f: Portugal, g: Romania, h: Spain)



(c)



(d)

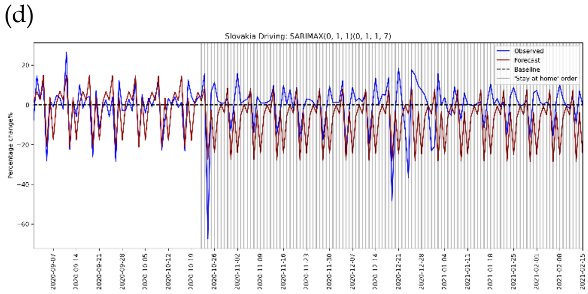
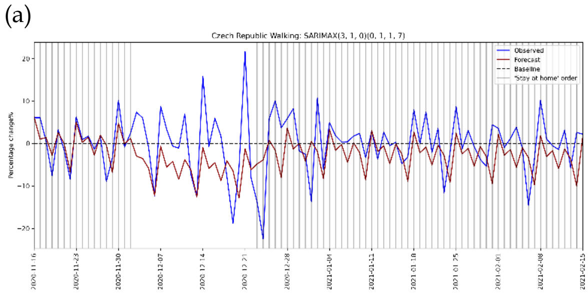
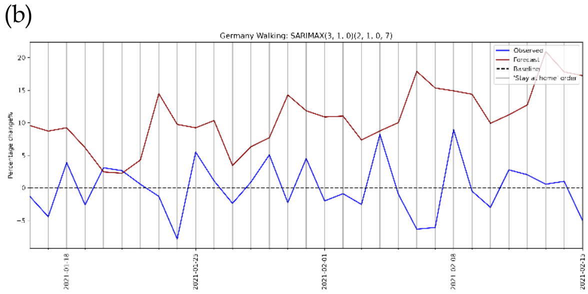


Figure 9. SARIMAX forecasts for driving in relation to "Stay at home" orders (a: France, b: Greece, c: Ireland, d: Slovakia)

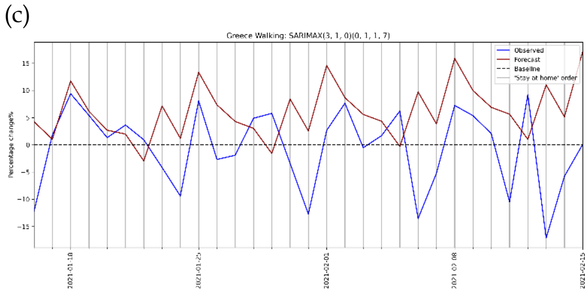
(a)



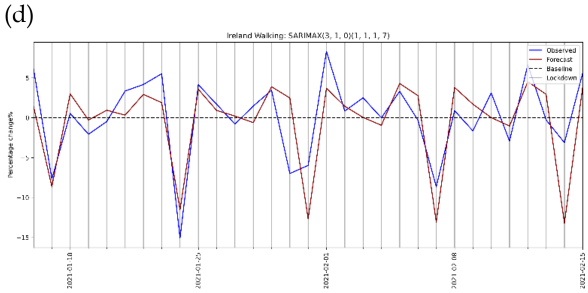
(b)



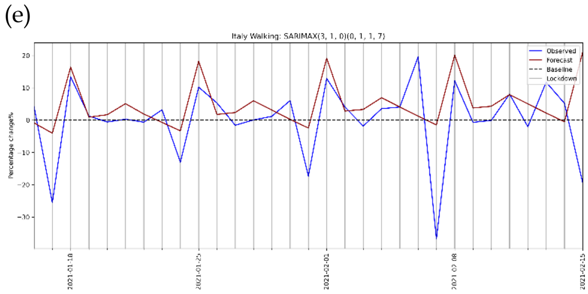
(c)



(d)



(e)



(f)

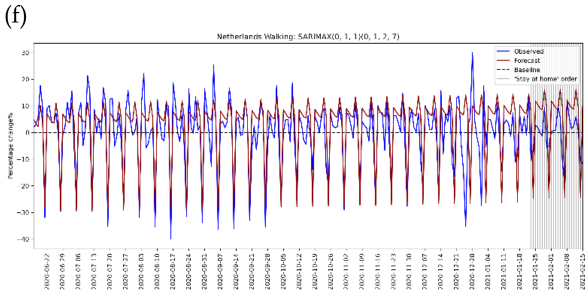
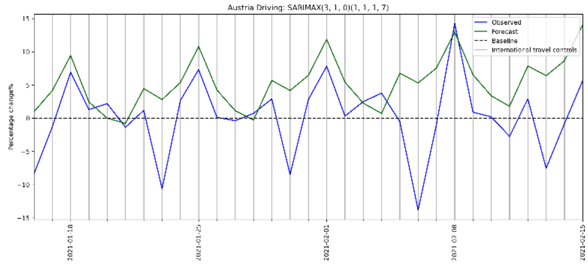
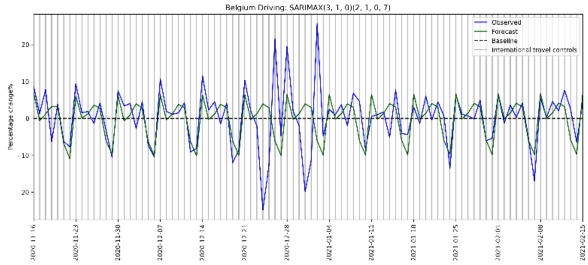


Figure 10. SARIMAX forecasts for walking in relation to "Stay at home" orders (a: Czech Republic, b: Germany, c: Greece, d: Ireland, e: Italy, f: Netherlands)

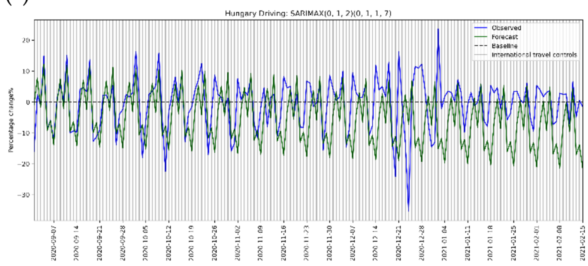
(a)

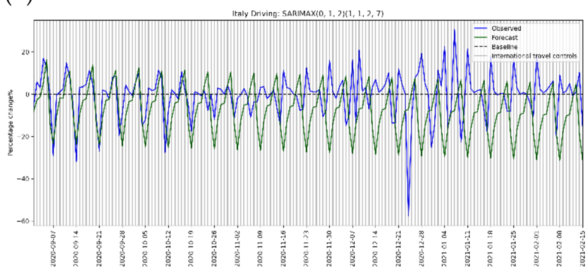
(b)



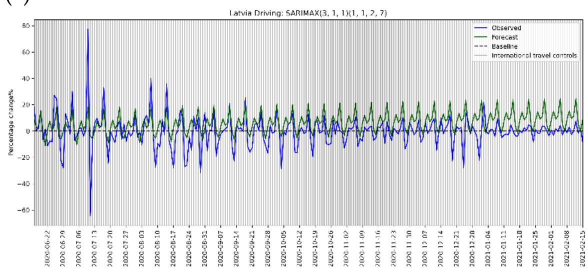


(c) (d)





(e) (f)



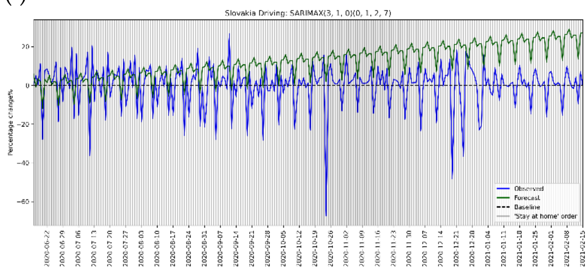
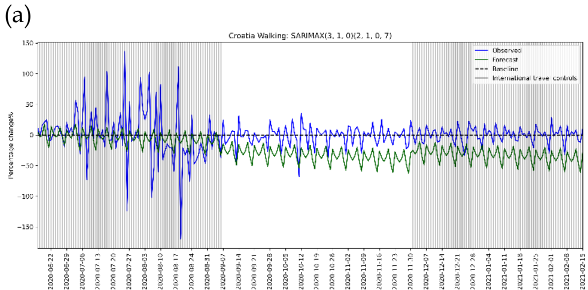
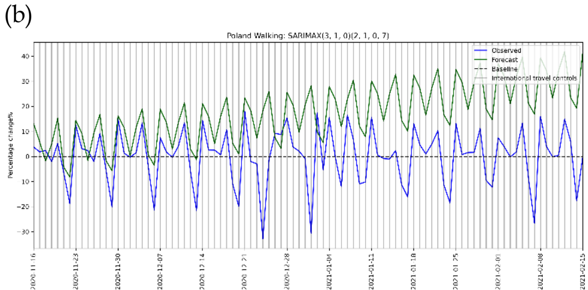


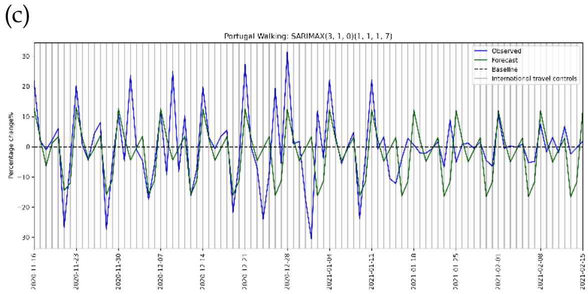
Figure 11. SARIMAX forecasts for driving in relation to International travel controls (a: Austria, b: Belgium, c: Hungary, d: Italy, e: Latvia, f: Slovakia)

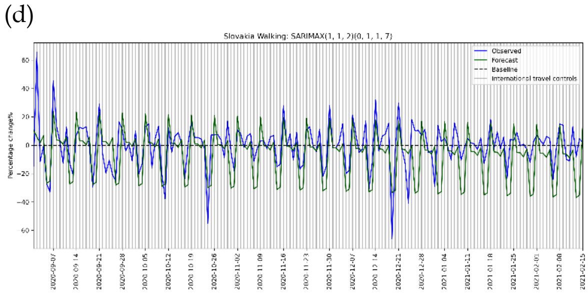
(a) (b)





(c) (d)





(e) (f)

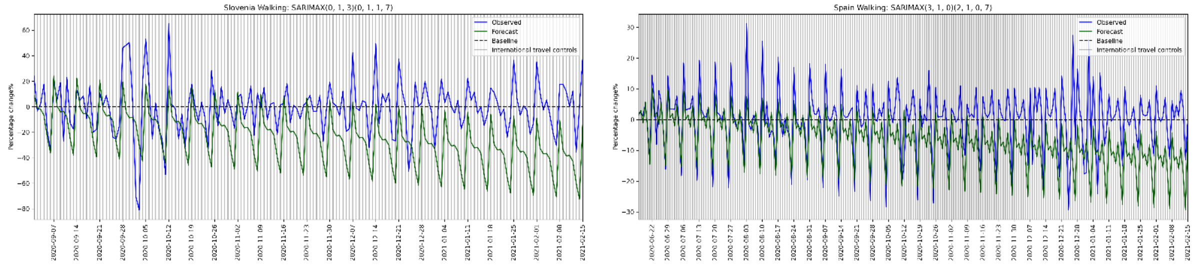


Figure 12. SARIMAX forecasts for walking in relation to International travel controls (a: Croatia, b: Poland, c: Portugal, d: Slovakia, e: Slovenia, f: Spain)

The visual inspection of the difference between the observations and the forecasted values, namely the residuals, is important in order to ensure a no bias in the forecasting method (Hyndman and Athanasopoulos, 2018). In Figure 13, the diagnostics plot of the residuals from the SARIMAX model for walking in relation to school closing in Austria is presented as an example, with a standardized over time residuals plot, a histogram plus estimated density of standardized residuals, along with the normal density plotted, a normal Q-Q plot, with the normal reference line and a Correlogram (Seabold and Perktold, 2010).

The top left plot shows no significant correlation in the residuals series, while the mean value is close to zero. In addition, this time plot does not display any obvious seasonality and appear to be white noise. The histogram on the top left plot suggests normal residuals, as the orange line follows closely the normal distribution. A normal indication of the residuals is also provided from the qq-plot, in which the residual distribution follows the linear trend of the samples taken from a standard normal distribution. The autocorrelation (i.e. correlogram) plot on the bottom right exhibits that the time series residuals have low correlation with lagged versions of itself. Similar insights are presented from the diagnostics plots of all SARIMAX models.

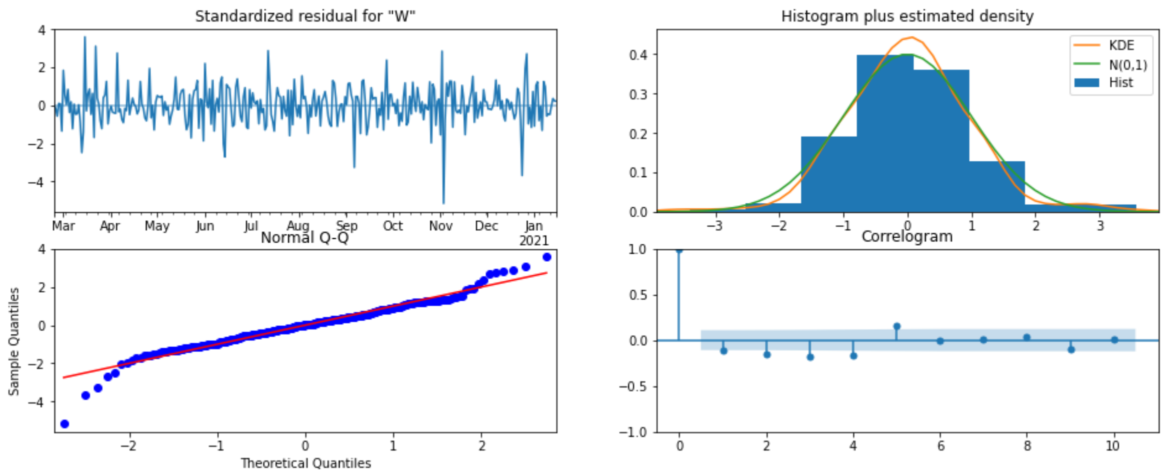


Figure 13. Residuals chart of SARIMAX model for walking in relation to school closing in Austria

6. Conclusions

In this section, the main outcomes of the current research are discussed. Forty SARIMAX models were developed in relation to national confinement measures in order to describe driving and walking during the first year of the pandemic of COVID-19.

Regarding endogenous variables, an equal number of models (20) was found for the relationship of restrictive policies with driving and walking time-series. In the opposite direction, not all the exogenous variables had the same results. It was revealed that the effect of "Stay at home" orders was not a significant factor for the evolution of people movements, as only 10 models were found to be linked to this policy. During the first months after the appearance of virus in Europe, there is an evident reduction of the outdoor mobility, as mentioned in the literature review (Bucsksy, 2020; Aloi et al., 2020), but progressively citizens are adapted into the new conditions and do not postpone necessary activities.

School closing proved to be a crucial determinant for the alteration of driving and walking traffic volumes, since this exogenous condition was modeled the most (18 SARIMAX models). It should be noted that schools' and universities' closures were usually applied as the first preventive measure, according to Hale et al. (2021), in periods of major outbreaks. Thus, this policy marked the beginning of high-risk periods and provoked public's fear. In addition, the halt of educational activities has an instant effect on students', as well as on families' mobility.

International travel controls were imposed to all countries, but affected mainly those with no further measures. When no other restrictive policies were applied and free movements were allowed, travel bans determined citizens' risk perception of mobility and led to reduced traffic flows. For example, Slovenia and Latvia, two of the countries with "no lockdown" strategy, obtained models only for this measure.

With respect to train and test set combinations, results show that as progressively more cases were executed and more train data were integrated, more statistically significant models were provided. This finding indicates that for most countries mobility during second "wave" could not be predicted only by the experience of the first months, but the summer easing of countermeasures or even the beginning of autumn pandemic outburst should also be considered. It should be noted that the available data corresponded to the first year of the pandemic in Europe. Including the proceeding months in the analysis, better and more precise outcomes could be provided.

Most of the models were found for Austria (3), Czech Republic (3), Hungary (3), Italy (3), Slovakia (3) and Spain (3). The stricter implementation of measures in those countries and the higher number of COVID-19 cases and casualties probably provoked public's fear of exposure, resulting to the reduction of outdoor activities. Specifically, Spain and Italy have suffered the most from the pandemic in numbers of confirmed cases and deaths, especially the first months of the appearance of the disease (Our World in Data, 2021). Moreover, Italy was the first country that imposed mandatory restrictions, the strictest in Europe, as the flags of the Oxford tracker (Hale et al., 2021) showed (e.g., minimal exceptions for leaving the house, forbidden daily exercise etc.).

It is important to note that few countries did not demonstrate any models. The different strategies of "no lockdown" (e.g., non-compulsory "stay at home" orders, recommendations to restrict activities etc.) in Finland, Sweden and Lithuania (until early December) had as result no statistically significant models with the available data. In addition, due to the brief imposed countermeasures in Estonia, it was not possible to model the relationship between those policies and the mobility patterns. At the same time, in Bulgaria and Luxembourg, various confinement measures were applied, but no significant models were found. As far as Luxembourg is concerned, the small population and the low standard deviations, as shown in Tables 2 and 3, are probably the reasons of no mobility models.

The fact that Bulgaria was not actually affected until the beginning of October (Our World in Data, 2021) could explicate the difficulty of modeling mobility in relation to the restrictive measures. During the first "wave", the surprise due to a new disease provoked a sharp decrease of mobility, despite the low numbers of confirmed cases and deaths. During the second "wave", the travel behavior was completely different, as the risk of the virus was underestimated and people move a lot. Similar results are observed in Greece, where the mobility and restrictive measures of the first "wave" were not able to predict the mobility of the second one, with the higher number of cases and deaths (Our World in Data, 2021). Statistically significant models were found only when the autumn driving and walking are incorporated in the train set (Case 4). These findings are in lined with the research of Truong and Truong (2021), which revealed that travel behavior is highly affected by the risk perception of the disease.

7. Discussion

This paper presents an investigative attempt to model the relationship between COVID-19 response measures and driving and walking behavior in twenty-five European countries. The main innovation of the research is the approach to compare a large number of countries through time-series modelling. Methodologically, seasonal ARIMA with exogenous regressors (SARIMAX) models were found to be the most appropriate technique to model mobility time-series and to compare travel behavior across Europe.

Results demonstrate the direct impact of the applied restrictive measures on travel behavior in the majority of European countries, underlining the alteration of mobility patterns due to the pandemic. The sharp decline of traffic in the spring of 2020 is linked to the national restrictive strategies, while the easing of the imposed measures contributed to the gradual increase of drivers and pedestrians flows in the summer of 2020. Confinement policies proved to be equally effective in reducing driving and walking volumes, implying an overall mobility drop that should be examined. From a visual inspections of the results (i.e. Figure 7 to 12), models perform well, close to the real observations of driving and walking patterns, along with minimum errors and therefore can be considered reliable. Although, one adequate strategy arises for every country, more than one best fitted models have been developed for some European countries, such as Austria (3), Czech Republic (3), Hungary (3), Italy (3), Slovakia (3) and Spain (3). This fact reveals that the interdependence between mobility and countermeasures varies in accordance with the national pandemic policies.

From a policy perspective, these findings are extremely worthy for the subsequent waves of COVID-19 cases or future crises. Through the estimated models, the current research suggests the most adequate strategies in pan-European and national level for controlling the disease spread. For example, governments along with traffic management centres can evaluate the different mobility evolutions and identify popular areas, where specific measures could be taken to restrict the spread of the virus. Trends in mobility and the corresponding correlation with COVID-19 countermeasures could also act as a surrogate for virus transmission especially in times when cases are increasing. Consequently, if mobility patterns are increasing, governments and local authorities could impose the most significant measures as these are shown by the developed models to stop the spread. By exploiting the results of the developed models, smartphone applications informing the general public on the most effective COVID-19 measures and the impact that potential crowding is going to have on public health and general wellbeing. The understanding of the different mobility evolutions with similar countermeasures would help decision makers to enforce or lift the confinement measures after the required period. Towards that end, local and regional observatories which observe mobility and disease trends could be initiated in order to proactively detect the effect of COVID-19 and other diseases and the relationship with mobility and the corresponding disease-restricting countermeasures. Since different mobility results imply also different severity of the countermeasures between countries, international guidelines could be set in order to declare the most effective countermeasures based on mobility patterns between countries, especially on those with close business and touristic relationships. Furthermore, the transferability of this study allows governments and policy makers to devise their pandemic response depending on the results of countries with similar demographic and geographic characteristics. Hence, the analysis could provide useful insights also for countries that were not studied in the current paper but present similar cultural, demographic and geographic attributes.

Finally, a smartphone application could be developed based on the previous insights to provide citizens appropriate advices for the crowding avoidance, by examining the response of countries with similar countermeasures.

Nevertheless, this paper is not without shortcomings. Utilized data from the mobility trend report of Apple are referred to a specific sample of drivers and pedestrians (i.e., users of Apple), which are only a sub-group of the national populations and may not resemble the total travel behavior. Apple does not hold demographic information of users and the representativeness of the sample compared to the general population is not available. Moreover, these data cover a short time span (i.e., February 2020 – February 2021) with only one day baseline (i.e. the 13th of January 2020) which dismisses the data seasonality within a year. An analysis of the traffic volumes during the pandemic compared to the previous years should be conducted to examine the magnitude of the impact due to the pandemic. Furthermore, the association of mobility with the confinement measures is important, but still indirect. Using the number of confirmed cases and deaths, the time-series models could have a better fit and provide better forecasts for the evolution of driving and walking during the pandemic.

Further research should consider the combination of restrictive measures, the strictness scale and the evolution of confirmed cases and deaths, as mentioned above, using multivariate forecasting models e.g., Vector AutoRegression (VAR) in order to gain further insights on the impact of COVID-19 on travel behavior. Moreover, expanding the time frame of the study and analyzing mobility of the next pandemic "waves" may provide better and more precise outcomes. Finally, an improved comparison between national strategies against the pandemic could be achieved through the examination of non-linearity and non-stationary features of the time-series.

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