

Statistical Analysis of Counter-Covid-19 Policies Adequacy and Effectiveness in Croatia

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Abstract: Countries around the world have imposed various counter-measures at national level, adjusting societal and economic activities to constrain the Covid-19 pandemic. Here we report the research results of assessment of adequacy and effectiveness of the Covid-19 pandemic counter-measures in the case study of the Republic of Croatia. Statistical analysis and inference methods are applied to identify the adequate national-level Covid-19 counter-measures, and their effective intensity levels, as a lessons-learned evidence with potential use for policy and strategy development support, in potential similar future situations.

Keywords: Covid-19, pandemic, counter-measures, adequacy, effectiveness.

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1. Introduction

The Covid-19 pandemic has exposed the world to unprecedented challenges of managing socio-economic processes at national and international levels. Countries have deployed various counter measures, adjusting societal and economic activities to constrain the pandemic.

Advances in information and communication sciences have allowed for collection, aggregation, and analysis of massive data sets of public health and societal activity indicators. Those include the structured observations of counter measures set on national levels to mitigate the pandemic.

Here we report the research aimed at assessment of adequacy and effectiveness of the Covid-19 pandemic counter measures in the case study of the Republic of Croatia. Adequacy is understood as the ability to enforce the targeted counter measure with the appropriate or productive intensity. Effectiveness is considered the ability of the counter-measure studied, and imposed at the adequate level of intensity, to counter the daily number of newly infected individuals at the national level. We also address of feasibility of utilization of a single socio-economic indicator, encompassing a number of specific ones, in association/correlation with the increase or decrease in number of new daily infections, nation-wide.

The presented research aims at identification of productive counter measures, and their productive intensity levels, as a lessons-learned experience with potential use for policy- strategy-development support, in potential similar future situations.

The manuscript reads as follows. Section 2 outlines studied counter measures and statistical methods used to assess their adequacy and effectiveness. Section 3 presents research results in the forms of figures and tables

with appropriate explanations. Section 4 discusses research results, outlines the conclusions drawn, and summarizes contributions of the presented research to the general understanding of the subject.

2. Method and material

Croatia has a population of 3.899 million. It is situated in south-eastern Europe, while extending a diverse topography, which determines Croatia's socio-economic framework, as depicted in Figure 1.

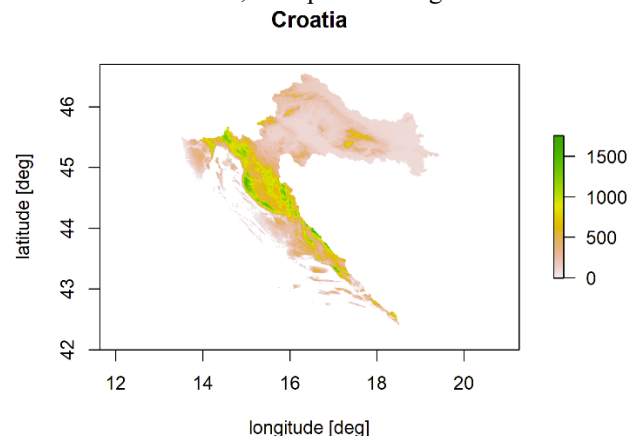


Fig. 1. Map of Croatia.

The economic profile of Croatia comprises activities yielding profit in tourism (15.9 % national GDP in 2021.[1]), agriculture and food industry.

Majority of Croatian citizens travel for the purpose of business, education, recreation, and health. Patterns of migrations range from daily migrations for work and business, weekend migrations for education (students traveling home from major cities where they study) and weekend recreations, and seasonal ones (tourism).

The Covid-19 counter measures in Croatia tackles physical gatherings of individuals with the specific/unique effects on social and economic activities nation-wide.



The first cases of COVID-19 in Croatia were reported in late February 2020. By late-January 2022, cumulative infections exceeded 899174 with about 13566 deaths. The previous peak of new daily cases was reached in mid-November 2021, with about 5527 new cases reported daily. Total number of reported cases was 1.27 million and deaths 18127.[2]

We utilize the daily number of new infections as collected by Our World in Data [2], and associate it with the database of counter measures and their intensity levels, as reported in database Coronavirus Government Response Tracker managed by University of Oxford. [3].

We identify adequacy and effect of the imposed counter measures, with the aim to identify those producing the containment results.

This Section outlines the methodology, and describes the original data used in the presented research.

2.1 Material

Data sets examined in the presented research comprises those collected from Websites Oxford Coronavirus Government Response Tracker [3] and from Our World in Data [2], with methodology and data description. Time series examined in the paper: (1) Daily number of new Covid-19 cases in Croatia (nc), (2)

Economic Support, Index (ESI) levels of provision of government funding assistance to economy and society, (3) Cancellation of Public Events (CPE) level imposed, (4) School Closing (SC) level, (5) Stringency Index – Average (SI), as a collated indicator of the imposed policies, (6) Restrictions on Gathering (RoG) level, (7) Closing Public Transport (CPT) level, and (8) International Travel Controls (ITC) level. Economic Support Index (ESI) is calculated on a scale of 0 to 100, with higher scores indicating more comprehensive and effective economic support provided by governments support to its citizens in response to the COVID-19 pandemic [4]. The ESI is a composite index that considers four main categories of economic support measures: income support, debt relief, fiscal measures, and monetary measures [4]. The Cancellation of Public Events (CPE) index is a measure developed by the Blavatnik School of Government at the University of Oxford to track the extent to which governments around the world have canceled or modified public events in response to the COVID-19 pandemic [4]. The CPE index is based on data collected from publicly available sources, including government websites, news reports, and social media [4].

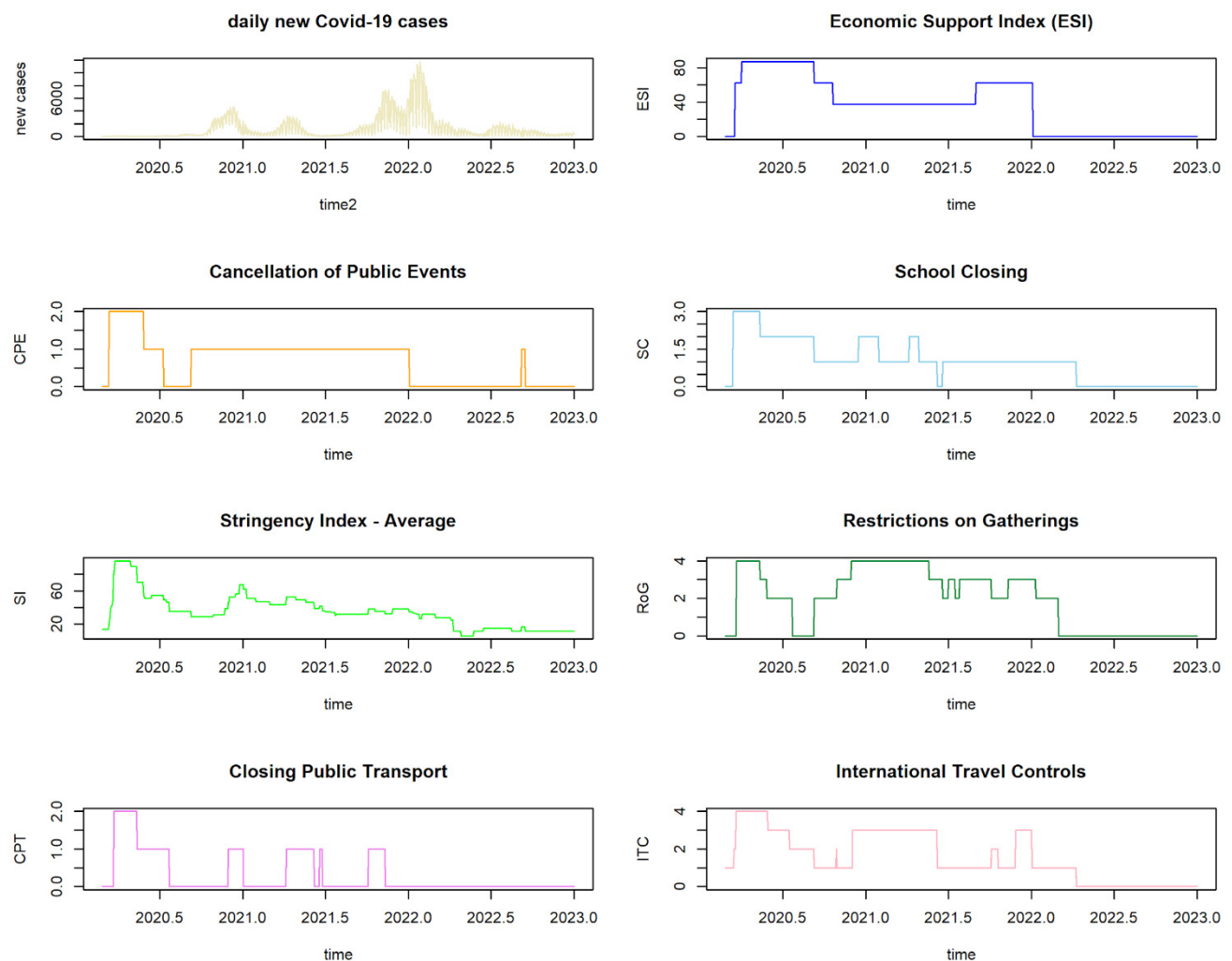


Fig. 2. Time series of indices considered.

The index is calculated on a scale of 0 to 100, with higher scores indicating more extensive cancellation or modification of public events [4]. The School Closing (SC) level is a system used to indicate the severity of measures implemented to close or partially close schools during a pandemic or other emergency situation [4]. The SC level is typically based on a scale from 0 to 4, with each level indicating progressively more severe measures from no closures or restrictions in place, schools are open and operating as usual (SC level 0) to the total closures or restrictions in place where schools are closed entirely and all learning takes place online (SC level 4) [4].

The Stringency Index (SI), developed by the Blavatnik School of Government, measures the strictness of government policies in response to the COVID-19 pandemic [4]. It uses a scale from 0 to 100, with higher scores indicating more stringent measures [4]. It is based on a composite measure of government policies that restrict people's behavior during the COVID-19 pandemic and combines nine response indicators, including school closures, workplace closures, travel bans, public events, and gathering restrictions, among others [4]. The Restrictions on Gathering (RoG) level is a system used to indicate the severity of measures implemented to restrict social gatherings during a pandemic or other emergency situation [4]. The RoG level is typically based on a scale from 0 to 4, with each level indicating progressively more severe restrictions from level 0 with no restrictions on gatherings in place to the level 4 with all gatherings prohibited [4]. Closing Public Transport (CPT) refers to the decision to suspend or stop public transportation services in a particular area, city, or country due to pandemic and security concerns [4]. The typical CPT levels are 0 - No measures, 1 - Recommend closing (or significantly reduce volume/route/means of transport

available) and 2 - Require closing (or prohibit most citizens from using it) [4]. International Travel Controls (ITC) measures include travel bans and quarantine requirements [4]. The ITC dataset is made from information on the implementation date, duration, and scope of the measures [4]. These measures are recorded on a scale from 0 to 4, where 0 indicates no restrictions and 4 indicates a complete ban on all international travel [4].

Time series of indices considered are shown together in the chart Figure 2.

A combined view of several results of exploratory statistical analysis is presented in Figure 3. The scatter-plot diagram is found in the lower triangle, which shows the fit between pairs of variables. Diagrams on diagonal depict estimates the experimental probability density function curve for every variable considered. The upper triangle contains correlograms of pairs of indices considered. None of the considered indices follows normal statistical distribution.

Statistical significance of the determined Pearson correlation coefficients is expressed in graphical terms based on the related statistical test p-values, as follows: (i) *** denotes $0 < p < 0.001$, (ii) ** denotes $0.001 < p < 0.01$, (iii) * denotes $0.01 < p < 0.05$, (iv). denotes $0.05 < p < 0.1$ and (v) no mark denotes $0.1 < p < 1$.

The analysis established that policy/measure indices are mostly categorical or discrete, except for SI, which can be expressed as a continuous variable. Overall, there is weak correlation between the target (nc) and the predictors (policy/measure indices), and modifications to policy/measure indices do not appear to have a substantial effect on the target variable.

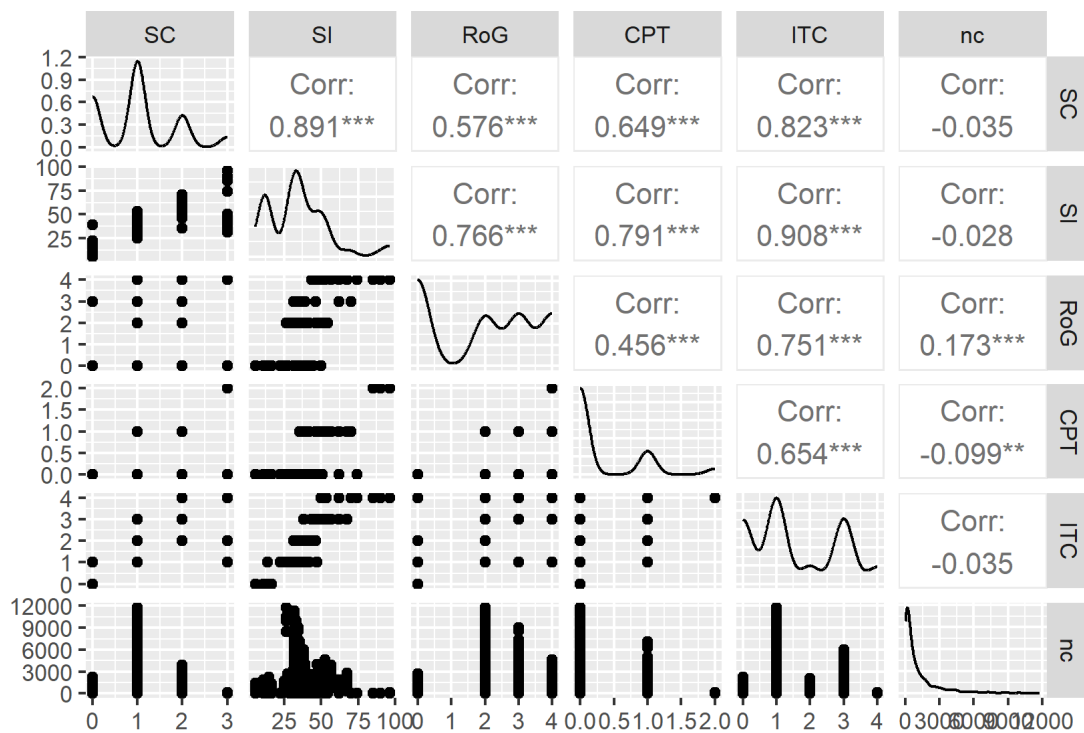


Fig. 3. Combined scatter-plot diagram, and correlogram of indices considered.

The high correlation between policy/measure indices suggests that they are interconnected and have a linear relationship. As a result, modifications to one policy/measure index could potentially affect the other indices. A normal distribution is commonly used to represent normal distributions, however, in this research, all the indices under consideration follow a non-Gaussian distribution, implying that the data may be skewed. The SI index summarizes the effects of individual policy/measure indices and it is hypothesized that there is a correlation between the target variable (nc) and the SI index. Therefore, changes to the SI index may have a more substantial impact on the target variable (nc) than changes to individual policy/measure indices.

2.2 Method

Time series of daily number of new Covid-19 cases in Croatia, and intensities of the eight counter-measures, listed in Section 2.1. are examined in the presented research.

Data are assessed using the common methods of exploratory statistical analysis, including the correlation analysis [5]. Inference on adequacy and effectiveness of counter-measures are drawn using examination of diagrams of pairs of time series, scaled to reveal the meaning. Time series of daily numbers of new Covid-19 cases is matched with the scaled time series of counter-measure intensities, separately.

Association between daily number of new Covid-19 cases in Croatia, and the Stringency Index, presumed a single indicator of the overall mitigation intensity by a set of countermeasures, is examined using correlation analysis [5], as well as using lagged Granger Causality Index [6]. Finally, statistical significance of every counter-measure intensity in description/prediction of daily number of new Covid-19 cases is examined by formal application of linear regression model development method [7].

The variable importance of the predictor is examined using Linear regression model (LRM) importance of predictors. [8] Variable importance is calculated as an absolute t-value obtained from Formal linear regression model.

3. Research results.

During the Covid-19 outburst in Croatia daily number of new cases was low. Still, Croatian government decided to impose very strict measures to counter the spread of the virus. This decision was made with the rationale of the unknown characterization of the virus and means of its spread.

Later phases of Covid-19 pandemic were not tackled with such a one-side approach, but in consideration of epidemiology, public health system, and socio-economic effects.

The presented research assesses adequacy and effectiveness of particular counter measures on the daily number of new Covid-19 cases through analysis of scaled time series diagrams of such pairs.

Scaled time series of Economic Support Index (ESI, blue line) and the daily number of new Covid-19 cases are depicted in Figure 4.

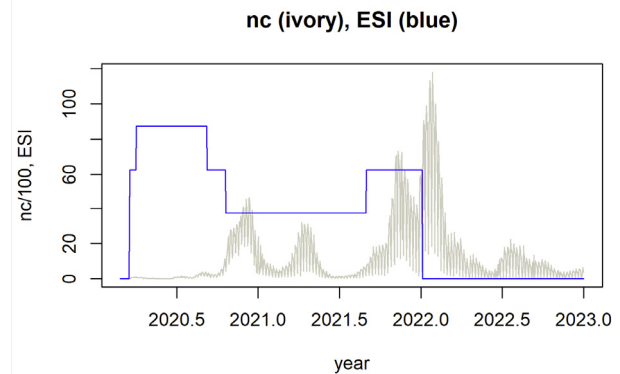


Fig. 4. Effects of economic support index.

Initially, the government decided to strongly support the economy in order to preserve the jobs. There were a significant number of businesses which involved close contact with larger numbers of people such as bars and restaurants that were closed. One of the aspects of this measure was also aimed to ease the acceptance of the lockdown. As the number of new cases continued to be low it was decided to open some of the businesses which enabled the government to lower the support. This resulted in an increased number of new cases. When the number of new cases increased rapidly the government decided to increase the support which was not as efficient as in the beginning of the pandemic when it mitigated the spread of the virus.

Scaled time series of the effect of school closure (SC, skyblue line) and the daily number of new Covid-19 cases are depicted in Figure 5. School closure at sufficient level (Level 2 and above), mitigates the transmission of disease. Lectures were mainly organized online with the exception of the exams. Since online lectures reduced the contact between lecturers and students, the quality of the process suffered. The government was closely monitoring the number of new cases and lowered the level of school closing with a decreased number of new cases. It can be seen that insufficient level of School closure may even instigate disease.

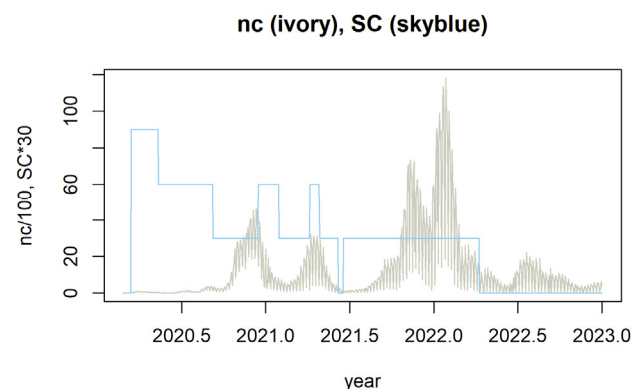


Fig. 5. Effects of school closure.

Time series of the effect of the Stringency Index (SI, green line) and the daily number of new Covid-19 cases are depicted in Figure 6. Stringency Index higher or equal to 60 tackles the outburst efficiently and successfully. Lower SI levels may be efficient on smaller outbursts.

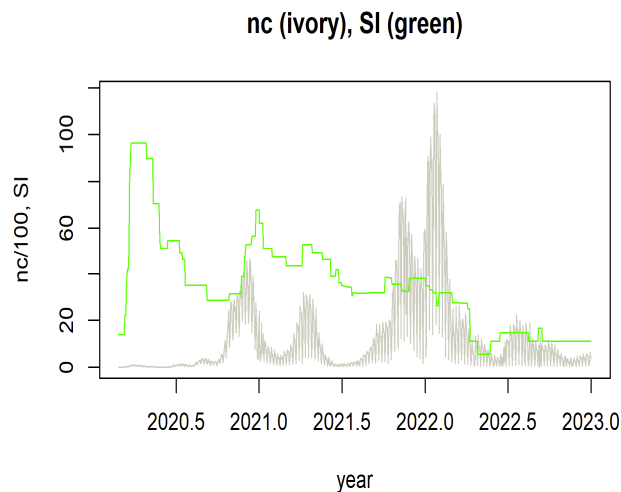


Fig. 6. Effects of stringency index – average.

Scaled time series of the effect of Reduction of Gatherings (RoG, spring green line) and the daily number of new Covid-19 cases are depicted in Figure 7. Level 3 and above may be seen as successful in mitigation of outbreaks. Lowering levels in situations of raising the number of infections produces counter effects, instigating the outbreak.

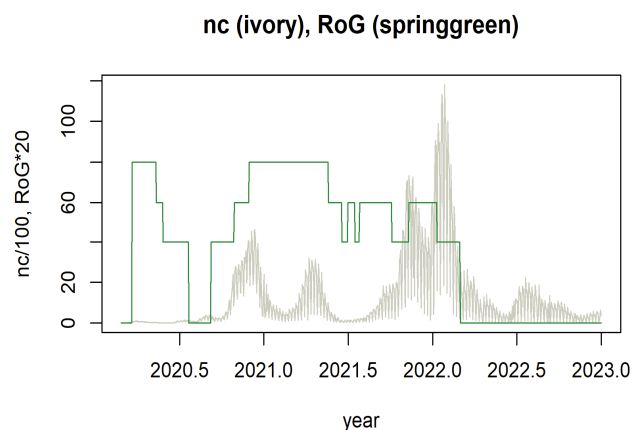


Fig. 7. Effects of reduction of gatherings.

Scaled time series of the effect of Closing Public Transport (CPT, violet line) and the daily number of new Covid-19 cases are depicted in Figure 8. Even a moderate level of public transport suspension appears as efficient in tackling the outbreak, despite the mandatory face masks usage.

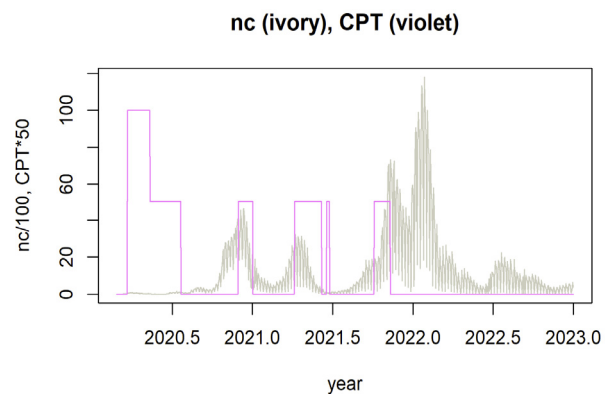


Fig. 8. Effects of closing public transport.

Scaled time series of the effect of International Traffic Controls (ITC, red line) and the daily number of new Covid-19 cases are depicted in Figure 9. A sufficient level (Level 3, or above) should be imposed to tackle the outbreak efficiently. ITC of a sufficient level should be imposed for a month, at least, to produce effect.

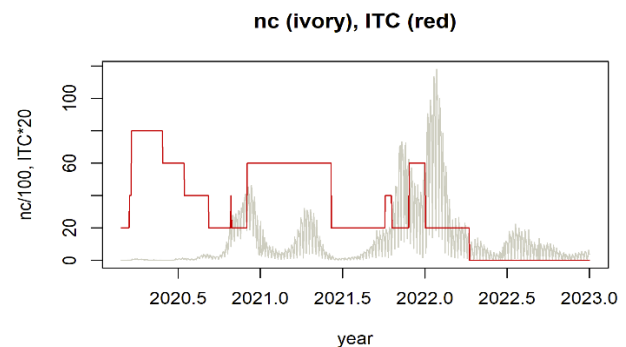


Fig. 9. Effects of international traffic controls.

The cause-effect relation between numeric indices of new cases and Stringency Index is examined using lagged Granger Causality Index, as depicted in Figure 10. No formal effects caused on the number of new cases by the Stringency Index was found.

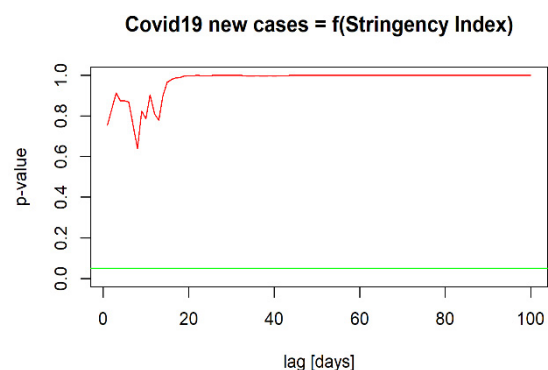


Fig. 10. Cause-effect relation between numeric indices nc and SI.

The cause-effect relation between numeric indices of Stringency Index and new cases is examined using lagged Granger Causality Index, as depicted in Figure 11. Formal effects of the number of new cases on Stringency Index found with a delay of approximately 3 months.

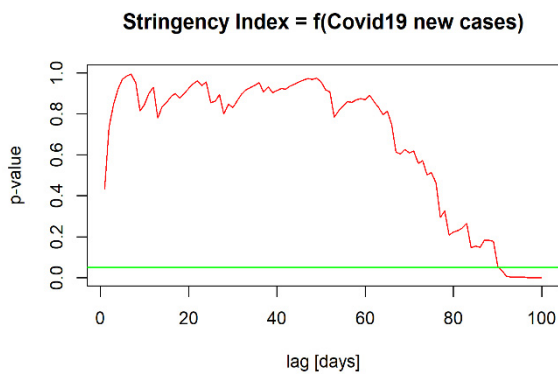


Fig. 11. Cause-effect relation between numeric indices nc and SI.

Analysis of the linear regression model of nc as a function of SI showed poor performance. SI is not a statistically significant predictor of nc. The Breusch-Godfrey test with a lag order of 10 was used to detect the presence of auto correlation in the residuals of a regression model. [9] Test result returned p-value less than 2.2×10^{-16} . Low p-value indicates that there is evidence of serial correlation in the residuals.

Furthermore, various structures of the linear regression models emphasize particular indicators over SI in description/prediction of daily number of new Covid-19 cases, and, consequently, the adequacy and efficiency of the applied counter-measures.

Formal Linear Regression Model with all predictors concerned was introduced. Results are depicted on Figure 12. Model gives a relatively good bias description. Model also gives poor variance description. Larger p-values suggest that CPT is not statistically significant and SI is barely significant.

```
Call:
lm(formula = nc ~ ., data = data)

Residuals:
    Min       1Q   Median       3Q      Max
-2654.0  -850.9  -386.8   211.0  8790.5

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 1377.122    170.916   8.057 2.14e-15 ***
ESI          -11.147     2.793  -3.991 7.05e-05 ***
CPE         -1428.211    166.072  -8.600 < 2e-16 ***
SC           936.887    182.337   5.138 3.31e-07 ***
SI           -30.982    12.968  -2.389 0.017064 *
RoG          956.153    68.093  14.042 < 2e-16 ***
CPT          276.319    181.227   1.525 0.127637
ITC          -388.745    102.940  -3.776 0.000168 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1659 on 1033 degrees of freedom
Multiple R-squared:  0.2102, Adjusted R-squared:  0.2048
F-statistic: 39.27 on 7 and 1033 DF, p-value: < 2.2e-16
```

Fig. 12. Formal Linear Regression Model with all predictors concerned.

Similar analysis was done with the CPT variable removed from the model, as depicted in Figure 13. This model gives a relatively good bias description. Model also gives poor variance description. Larger p-values suggest that SI is not statistically significant.

```
Call:
lm(formula = nc ~ ESI + CPE + SC + SI + RoG + ITC, data = data)

Residuals:
    Min       1Q   Median       3Q      Max
-2685.9  -852.9  -401.9   253.0  8832.2

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 1203.652    127.629   9.431 < 2e-16 ***
ESI          -10.652     2.776  -3.837 0.000132 ***
CPE         -1427.274    166.177  -8.589 < 2e-16 ***
SC           830.441    168.550   4.927 9.72e-07 ***
SI           -17.534     9.512  -1.843 0.065566 .
RoG          910.022    61.041  14.908 < 2e-16 ***
ITC          -412.490    101.820  -4.051 5.48e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1660 on 1034 degrees of freedom
Multiple R-squared:  0.2084, Adjusted R-squared:  0.2038
F-statistic: 45.37 on 6 and 1034 DF, p-value: < 2.2e-16
```

Fig. 13. Formal Linear Regression Model with all predictors concerned, except CPT.

Similar analysis was done with the CPT and SI variable removed from the model, as depicted in Figure 14. This model gives a relatively good bias description. Model also gives degraded variance description ability. All predictors are statistically significant.

```
Call:
lm(formula = nc ~ ESI + CPE + SC + RoG + ITC, data = data)

Residuals:
    Min       1Q   Median       3Q      Max
-2802.3  -865.8  -430.6   267.7  8895.9

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 1033.323    88.141  11.724 < 2e-16 ***
ESI          -9.357     2.689  -3.480 0.000522 ***
CPE         -1553.417    151.608  -10.246 < 2e-16 ***
SC           622.321    125.292   4.967 7.95e-07 ***
RoG          883.977    59.452  14.869 < 2e-16 ***
ITC          -507.517    87.907  -5.773 1.03e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1662 on 1035 degrees of freedom
Multiple R-squared:  0.2058, Adjusted R-squared:  0.202
F-statistic: 53.64 on 5 and 1035 DF, p-value: < 2.2e-16
```

Fig. 14. Formal Linear Regression Model with all predictors concerned, but CPT, SI.

Linear regression model (LRM) importance of predictors is depicted in Figure 15.

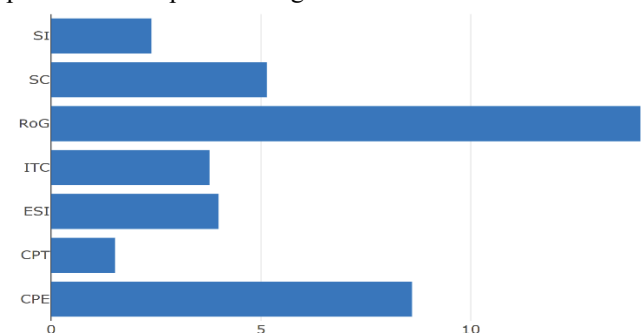


Fig. 15. LRM importance of predictors.

Importance of predictors is calculated as an absolute t-value from Formal Linear Regression Model with all predictors concerned.

Reduction of Gatherings and Cancellation of Public Events are the most efficient policies in tackling outbreaks. Imposing the others may have the expected

and wanted effects, when applied in particular timing, and the enforcement level.

4. Discussion and conclusion.

The presented research aimed at identification of productive counter measures, and their productive intensity levels, as a lessons-learned experience with potential use for policy- strategy-development support, in potential similar future situations.

The presented research aimed at assessment of adequacy and effectiveness of the Covid-19 pandemic counter measures in the case study of the Republic of Croatia. Scaled time series of the counter measures were compared with a number of new cases to assess adequacy of each countermeasure. Statistical significance of effectiveness of a counter-measures was assessed with Formal Linear Regression model. Reduction of Gatherings and Cancellation of Public Events are the most efficient policies in tackling Covid-19 outbreaks.

References

- [1] Ministry of Tourism and Sports of the Republic of Croatia, (2022). *Turizam u brojkama 2021*. Available at: https://mint.gov.hr/UserDocsImages/2022_dokumenti/Turizam%20u%20brojkama%202021.pdf, Accessed on April 23, 2023.
- [2] Mathieu E., Ritchie H., Rodés-Guirao L., Appel C., Giattino C., Hasell J., Macdonald B., Dattani S., Beltekian D., Ortiz-Ospina E. and Roser M. (2020). *Coronavirus Pandemic (COVID-19)*. Available at: <https://ourworldindata.org/coronavirus>, Accessed on April 23, 2023.
- [3] OxCGRT project. (2023). *Oxford Coronavirus Government Response Tracker (OxCGRT) data*. Available at: <https://github.com/OxCGRT>, Accessed on February 12, 2023.
- [4] Hale, T. et al. (2022). *Variation in government responses to COVID-19 BSG-WP-2020/032 Version 14.1*. Blavatnik School of Government, University of Oxford. Oxford, UK. Available at: <http://www.bsg.ox.ac.uk/covidtracker>, Accessed on February 12, 2023.
- [5] Mills, T. C. (2019). *Applied Time Series Analysis: A Practical Guide to Modeling and Forecasting*. Academic Press. London, UK.
- [6] Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, 37(3), 424–438. doi:10.2307/1912791.
- [7] Montgomery D. C., Peck E. A. and Vining G. G. (2012). *An Introduction to Linear Regression Analysis*. John Wiley & Sons, Inc.
- [8] Thomas, D.R., Hughes, E. and Zumbo, B.D. (1998). On Variable Importance in Linear Regression. *Social Indicators Research* 45, pp. 253–275, <https://doi.org/10.1023/A:1006954016433>
- [9] Breusch, T.S. and Godfrey, L.G. (1978) Misspecification Tests and Their Uses in Econometrics. *Journal of Statistical Planning and Inference*, 49, pp. 241-260, [https://doi.org/10.1016/0378-3758\(95\)00039-9](https://doi.org/10.1016/0378-3758(95)00039-9).