Czech Anti-Covid Rules Evaluation

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Abstract. We present a retrospective analysis of the efficaciousness of Czech anti-COVID state rules during the first quarter of 2022. This analysis focuses on a specific time window from our four-year evaluation of various restrictive measures implemented by the Czech government, examining long-term data from the first three COVID-19 cases detected in early March 2020 through to September 2024. It traces the evolution from the initial intense response to the virus to the eventual normalization of COVID-19 as a common issue. Our study utilizes an adaptive recursive Bayesian stochastic multidimensional model to predict key COVID-19 metrics from nine essential data series. This model distinguishes between effective measures and those merely disruptive or mistimed. Additionally, it predicts crucial statistics such as hospitalizations, deaths, and symptomatic cases, offering valuable insights for the daily management of anti-COVID measures, necessary precautions, and future pandemic recommendations.

Keywords: COVID-19 · Recursive forecasting model · Bayesian learning · Adaptive multistep predictor · Anti-pandemic measures

1 Introduction

Recent lifestyle changes, such as increased global travel and urbanization, have accelerated the spread of infectious diseases, enabling them to rapidly escalate into global pandemics. COVID-19, a novel virus with exponential transmission, impacted more than 178 countries and resulted in over 6 million deaths. The initial lack of knowledge about the virus led to disorganized and often chaotic responses from governments worldwide. The hastily implemented measures varied significantly both between and within countries, reflecting different stages of the epidemic, as well as variations in resources, cultures, governance, and legal frameworks. For instance, school closures alone sent over half a billion children home, according to UNESCO (United Nations Educational, Scientific and Cultural Organization) [1]. Several studies and articles [1–9] have sought to assess the effectiveness of government-imposed measures. However, the full impact of interventions such as lockdowns, curfews, mask mandates, and other restrictions remains insufficiently understood, highlighting the need for further research to

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enhance responses to future global pandemics. Flaxman et al. [2] on 11 European countries found that lockdowns were the most effective measure in reducing the reproduction number R over four months. In contrast, measures like school and university closures, case-based isolation, bans on large public events, and social distancing were found to be less effective. However, this conclusion is contested by the study conducted by Soltesz et al. [5]. A similar study by Brauner et al. [6] examined eight mandatory non-pharmaceutical interventions implemented across 41 countries over a four-month period, using data on confirmed COVID-19 cases and deaths from the Johns Hopkins CSSE COVID-19 Dataset. The effectiveness of these measures was assessed as a percentage reduction in the reproduction number R, using a modified Bayesian model from Flaxman et al. [2]. The study found significant reductions in R associated with closing all educational institutions, limiting gatherings to 10 people, and shutting down face-to-face businesses, while stay-at-home orders had a negligible effect. Shinde et al. [4] conducted a survey of key statistical, analytical, mathematical, and medical parameters, highlighting the complexities of pandemic modeling and offering recommendations for improvement. Pradhan et al. [3] reviewed historical viral pandemics, emphasizing the importance of preventive measures. Perra [7] analyzed 348 articles on COVID-19, focusing on the effects of non-pharmaceutical interventions, behavioral responses, and changes in medical practice. Athreya et al. [10] examined COVID-19 models developed in India, primarily variants of the SEIR compartment model, noting that predictions were often limited by poor data quality. A log-linear Poisson autoregression model [11] is used to analyze COVID-19 contagion dynamics based on newly reported infection counts. Additionally, a polynomial regression model for positive cases [12] has been validated with data from four countries but fails to detect new pandemic waves or evaluate external interventions. The modified standard SEIR model [13], using an approximate Bayesian solution, explores alternative timings and non-pharmaceutical interventions during the initial spring wave of the pandemic in Czechia, informed by estimated sociological data. Additionally, the impact of non-pharmaceutical measures in four regions of Saudi Arabia is illustrated with the SEPAIHR compartment model [8]. We also proposed a two-dimensional random vector model for analyzing time-series COVID-19 data [14]. Furthermore, a framework for implementing a prospective real-time machine learning-based early warning system to predict or confirm COVID-19 outbreaks based on fluctuations in the effective reproductive number is outlined in [9]. A recent review of COVID-19 research, data, and modeling can be found in [15].

The study's objectives and contributions are outlined below:

- Retrospectively analyze unusually long three-year period of observed time series data (illustrated on the selected quarter-year period due to page limit) on the COVID-19 epidemic to evaluate the effectiveness and timing of governmental anti-COVID measures.
- Forecast critical COVID-19 metrics, including the number of hospitalizations, fatalities, and symptomatic cases.

- Utilize an adaptive recursive Bayesian model [14] that efficiently leverages the mutual correlations among various long-term disease time series to assess the specified COVID-19 epidemic period.

The significance of this study is underscored by the substantial number of COVID-19 deaths in the country, as depicted in Fig. 1.

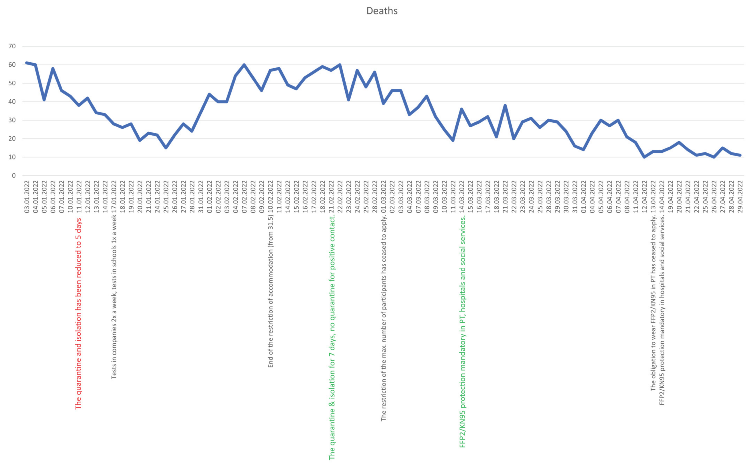

Fig. 1. The daily COVID-19 death toll in Czechia from winter 2022 to spring 2022.

2 Covid Model

The COVID-19 predictive and adaptive model allows the prediction of future significant COVID-19 statistics for efficient care planning and detection of the impact of anti-COVID measures. Modeling general multi-time-series data necessitates the use of two-dimensional random vector models to accurately capture time-series correlations. One key advantage of the 2D Vector Causal Autoregressive Models (VCAR) (1) is their capacity for analytical solutions under several additional, yet reasonable, assumptions. A dedicated Gaussian noise-driven VCAR random vector model is employed to analyze multi-time-series COVID-19 data [14]. Let the digitized time series Y be indexed on a finite rectangular two-dimensional $N \times d$ lattice I, where N represents the overall time interval, t denotes the time index, and d indicates the number of time series being modeled simultaneously. The VCAR random vector consists of a family of random variables with a joint probability density defined over all possible realizations Y of the $N \times d$ lattice I, subject to the following conditions:

$$p(Y \mid \theta, \Sigma^{-1}) = \frac{|\Sigma^{-1}|^{\frac{(N-1)}{2}}}{(2\pi)^{\frac{d(N-1)}{2}}} \exp\left\{ -\frac{1}{2} tr \left\{ \Sigma^{-1} \begin{pmatrix} -I \\ \theta^T \end{pmatrix}^T \tilde{V}_{T-1} \begin{pmatrix} -I \\ \theta^T \end{pmatrix} \right\} \right\} \quad , \qquad (1)$$

$\tilde{V}_{t-1} = \begin{pmatrix} \tilde{V}_{yy(t-1)} & \tilde{V}_{xy(t-1)}^T \\ \tilde{V}_{xy(t-1)} & \tilde{V}_{xx(t-1)} \end{pmatrix}$, where the term used is $\tilde{V}_{uz(t-1)} = \sum_{k=1}^{t-1} U_k Z_k^T$. The 2D VCAR model can be represented as a stationary causal uncorrelated noise driven 2D autoregressive process: $Y_t = \theta X_t + e_t$, where θ is the $d \times d\eta$ parameter matrix $\theta = [A_1, \ldots, A_\eta]$, $\eta = card(I_t^c)$, I_t^c is a causal neighbourhood, e_t is a Gaussian white noise vector with zero mean and a constant, yet unknown, covariance matrix Σ and X_t is the corresponding vector of Y_{t-s} (design vector). Choosing the right support for the VCAR model is essential for accurate modeling results. A contextual neighborhood that is too small may miss important details, while including too many neighbors can increase computational complexity and introduce noise, potentially degrading model performance. The optimal neighborhood can be identified using the Bayesian decision rule [16], which seeks to minimize the average probability of decision error. Parameter estimation (2) for the VCAR model using the Bayesian method with a normal-Wishart prior can be derived analytically:

$$\hat{\theta}_{t-1}^T = V_{xx(t-1)}^{-1} V_{xy(t-1)} \ , \tag{2}$$

where $V_{uz(t-1)} = \tilde{V}_{uz(t-1)} + V_{uz(0)}$ and $V_{uz(0)}$ represents the corresponding matrices from the normal-Wishart parameter prior. The one-step-ahead predictor for the normal-Wishart parameter prior is

$$E\left\{Y_t \,|\, Y^{(t-1)}\right\} = \hat{\theta}_{t-1} X_r \ , \tag{3}$$

and the corresponding prediction error

$$\epsilon_t = Y_t - E\left\{Y_t \,|\, Y^{(t-1)}\right\} = Y_t - \hat{\theta}_{t-1} X_t \ . \tag{4}$$

Measure5 is assessed using the absolute value of the prediction error slope angle. If the angle is greater than $45°$, it reflects the median of the prediction error from the actual day to the following five days; otherwise, it represents the average. The influence of the measure, denoted as Ξ, is derived from the Measure5 values as follows:

$$\Xi \begin{cases} > 2.5 \frac{\sum_{\forall t \in I} |Measure5_t|}{card(\forall t \in I)}, & \text{strong effect;} \\ \in \left\langle 1.6 \frac{\sum_{\forall t \in I} |Measure5_t|}{card(\forall t \in I)}; 2.5 \frac{\sum_{\forall t \in I} |Measure5_t|}{card(\forall t \in I)} \right\rangle, & \text{medium effect;} \\ \in \left\langle 0.6 \frac{\sum_{\forall t \in I} |Measure5_t|}{card(\forall t \in I)}; 1.6 \frac{\sum_{\forall t \in I} |Measure5_t|}{card(\forall t \in I)} \right\rangle, & \text{small effect,} \end{cases} \tag{5}$$

where I is the corresponding time interval for the Measure5 evaluation. We use the measure influence Ξ to differentiate between positive and negative anti-COVID-19 measures, while the black-colored measures have low Ξ. The estimates (2)–(4) are evaluated recursively (see [16] for details). The effective reproduction number (R number) is a key statistic for forecasting the future

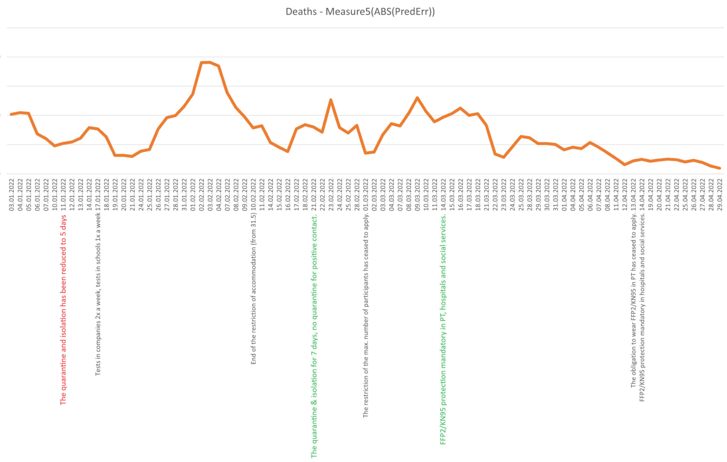

Fig. 2. The absolute value of the Measure5 (5) related to deaths during the winter 2022 wave of COVID-19 through spring 2022.

trajectory of a pandemic, as it reflects the influence of external measures. In contrast, the primary reproduction number is calculated without accounting for external interventions. In the VCAR model, we utilize a straightforward yet robust algorithm for calculating the R number, as outlined in [14].

3 Czech Covid Data

Czech COVID-19 data is publicly accessible on the Ministry of Health of the Czechia's webpage at https://onemocneni-aktualne.mzcr.cz/api/v2/covid-19. These data have been accessible since December 31, 2019, and are updated to the present day. The dataset includes daily figures for new cases, PCR tests, antigen tests, deaths, cumulative deaths, cumulative cases, recoveries, cumulative recoveries, active cases, hospitalizations, severe hospitalizations, first doses of vaccination, cumulative first doses, second doses, cumulative second doses, third doses, cumulative third doses, fourth doses, cumulative fourth doses, and some additional metrics. Note that some data series, such as vaccinations, are unavailable for the entire time interval N.

4 Last Czech Anti-Covid Rules

The first three cases of COVID-19 in the Czech Republic were reported on March 1, 2020. From March 2, 2020, to April 14, 2022, covering 1,035 days, the Czech government introduced over 70 anti-COVID measures, averaging approximately one measure every two weeks. In addition to these nationwide initiatives, various local authorities implemented additional measures, that are not included in this

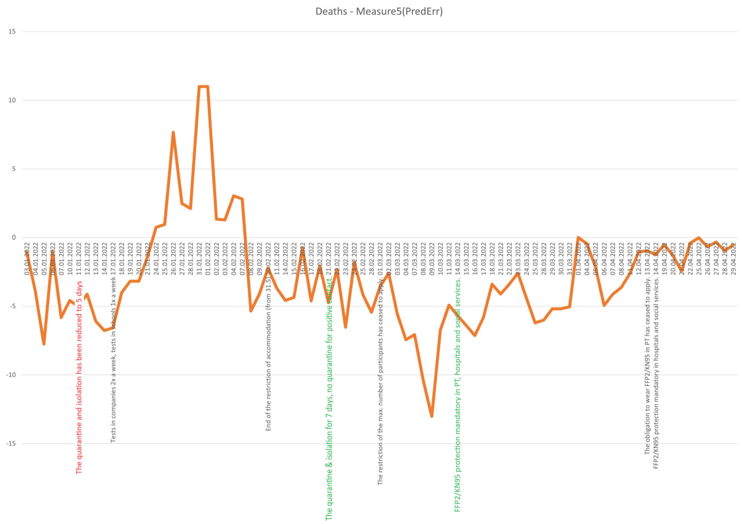

Fig. 3. The death Measure5 (5) from the winter 2022 wave of COVID-19 through spring 2022.

analysis. The measures encompassed school closures, business restrictions, border closures, curfews, lockdowns, mandatory use of respirators, five vaccination doses, and other interventions.

01.03.2020 The first three cases in the Czechia.

⋮

22.12.2021 Specific measures for Christmas and New Year's Eveinclude a maximum of 1,000 seated attendees at cultural or similar events, and a limit of 100 participants for events without seated arrangements. From December 29 to January 2, special contact restrictions will be enforced during New Year's Eve. The number of people allowed at a restaurant table will be reduced from six to four, and gatherings will be limited to a maximum of 50 attendees.

11.01.2022 The quarantine and isolation period has been reduced to five days.

17.01.2022 Employees in all companies are required to be tested twice a week, while students and teachers in schools must be tested once a week. This requirement also applies to vaccinated individuals and those who have previously contracted COVID-19.

10.02.2022 The obligation to show a certificate of completed vaccination or having experienced COVID-19 in the last 180 days in restaurants, services or at mass events has been abolished. The government thus responded to the decision of the Supreme Administrative Court, which canceled the measure on February 9.

19.02.2022 The isolation period has been extended from five to seven days. Conversely, individuals will no longer be required to quarantine after contact with someone who has tested positive.

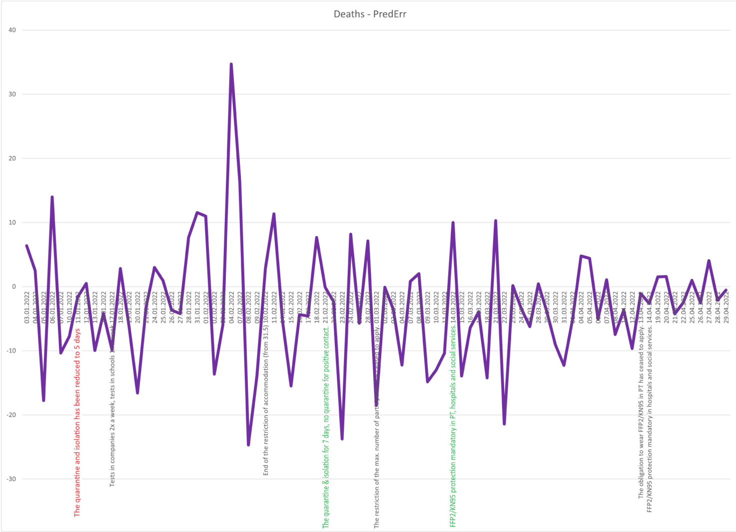

Fig. 4. The prediction error for deaths from the winter 2022 wave of COVID-19 through spring 2022.

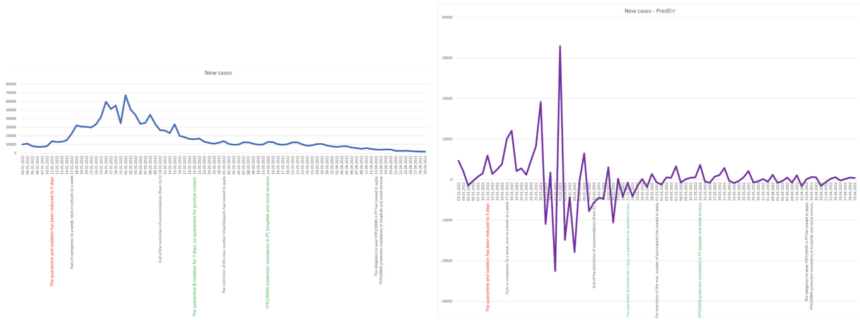

Fig. 5. The new infected from the winter 2022 wave of COVID-19 to the spring 2022 (5a left)and the corresponding prediction error (5b right).

01.03.2022 The restriction setting the maximum number of participants at mass events has ceased to apply.

14.03.2022 The requirement to wear a respirator in most indoor spaces has been lifted. The obligation remained only for public transport, trains, hospitals and social service facilities.

14.04.2022 The requirement to wear a respirator on public transport and trains has been lifted. However, masks remain mandatory in hospitals and social service facilities.

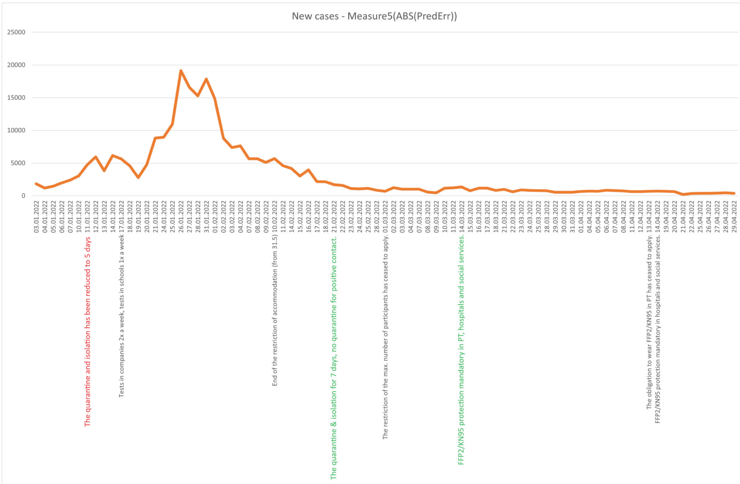

Fig. 6. The absolute value of Measure5 (5) for new infections from the winter 2022 wave of COVID-19 through spring 2022.

5 Results

Our model effectively identifies changes in the COVID-19 pandemic and assesses the impact of various anti-COVID measures-both positive and negative-along with the strength of their influence. However, polymerase chain reaction (PCR) test results for COVID-19 are often delayed by several days, which can adversely affect the number of detected positive cases and the precision of our modeling. The quality, reliability, and consistency of the reported COVID-19 data often need improvement. In all figures, red indicates the influence of negative anti-COVID measures, green represents positive measures, and black denotes measures that were mostly nuisances without any observable effect. Fig. 1 demonstrates the negative impact of shortening the COVID-19 quarantine on daily death counts. The number of daily COVID-19 deaths decreased when the government reverted to the original seven-day isolation period in spring 2022. Figure 4 shows the prediction error for deaths, and Fig. 2 depicts the absolute value of Measure5 (5). The graph in Fig. 3 illustrates the adverse impact of reducing the quarantine and isolation period to five days on January 11, 2022. The graphs in Fig. 5 illustrate the rapid surge in new cases detected following the implementation of mandatory testing twice a week for employees in all companies and students in schools, which began on January 17, 2022. Once the previously undetected cases were identified, the number of new cases returned to prior levels within two weeks. The selected instances of Measure5 (5) are depicted in Figs. 6 and 7.

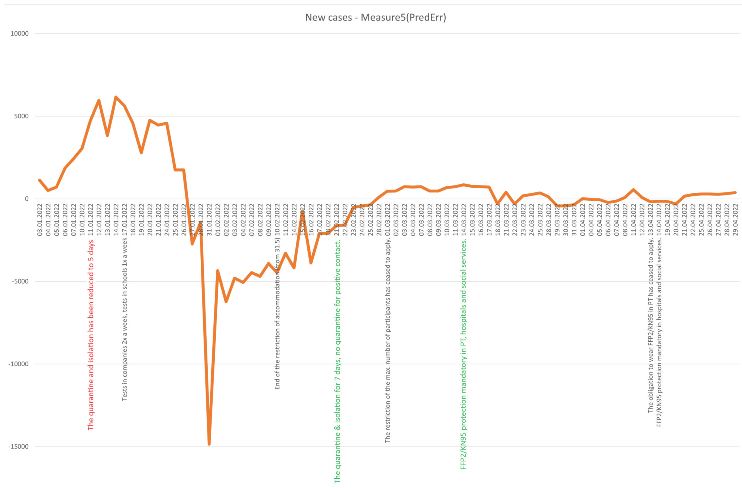

Fig. 7. The Measure5 (5) for new infections during the winter 2022 wave of COVID-19 through spring 2022.

6 Conclusions

The VCAR model presented here assesses the effectiveness of country-wide governmental anti-COVID measures during the spring 2022 period, selected from our overall observation window spanning from March 1, 2020, to October 2023. This period captures the shift from a dramatic struggle against an unknown illness to a more resigned approach, where COVID-19 is treated as an everyday inconvenience. Our model assesses the timing and impact of these measures through Bayesian adaptive prediction error estimations, utilizing nine publicly available COVID-19 data series. The retrospective analysis of selected Czech anti-COVID measures reveals examples of both effective and poorly timed interventions. The model differentiates between genuinely effective measures and those that were ineffective or had minimal impact. Additionally, the COVID-19 model offers predictions for key statistics, including the number of hospitalizations, deaths, and symptomatic cases. These forecasts can aid in the daily management of anti-COVID measures, inform necessary precautions, and assist in developing recommendations for controlling future pandemics. Our coming publication will contain an overall analysis of the unique three-year COVID analysis and a comparison of nearby country anti-COVID measures.

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