Research Article Summary:
Inferring COVID-19 spreading rates and potential change points for case number forecasts

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Introduction. When faced with the outbreak of a novel epidemic like COVID-19, rapid response measures are required by individuals as well as by society as a whole to mitigate the spread of the virus. During this initial, time-critical period, neither the central epidemiological parameters, nor the effectiveness of measures like cancellation of public events, school closings, and social distancing are known.

Rationale. As one of the key epidemiological parameters, we infer the spreading rate λ from confirmed COVID-19 case numbers at the example in Germany by combining Bayesian inference with a SIR (Susceptible-Infected-Recovered) model from compartmental epidemiology. Our analysis characterizes the temporal change of the spreading rate and, importantly, allows us to identify potential change points and provide short-term forecast scenarios based on various degrees of social distancing. A detailed, educational description is provided in the accompanying paper, and the model, inference, and prediction are available on github. While we apply it to Germany, our code can be readily adapted to any other country or region.

Results. In Germany, political interventions to contain the outbreak were implemented in three steps over three weeks: Around March 8, large public events like soccer matches were cancelled. On March 15, the closing of schools and other educational institutions along with the closing of non-essential stores were announced and implemented on the following day. One week later, on March 22, a far-reaching contact ban ("Kontaktsperre"), which includes the prohibition of even small public gatherings as well as the further closing of restaurants and non-essential stores was imposed by the government authorities.

From the observed case numbers of COVID-19, we can quantify the impact of these measures on the spread (Fig. 1). As of April 1, we have evidence of a first change point in the spreading rate from $\lambda_0 = 0.41$ (95 % Confidence interval (CI): [0.35, 0.49]) to $\lambda_1 = 0.25$ (CI: [0.20, 0.29]), which occurred around March 8 (CI: March 5 to March 10). Moreover, we have first indications for a second change point to $\lambda_2 = 0.13$ (CI: [0.10, 0.17]), which occurred around March 16 (CI: March 15 to March 18). Both changes in λ slowed the spread of the virus, but still imply exponential growth (Fig. 1, red and orange traces). To contain the disease spread, and turn from exponential growth to a decline of novel cases, a further decrease in λ is necessary.

As of April 1, we do not have sufficient observations to infer the time and magnitude of the expected third change point, because of the delay between infection, case report, and inferred evidence of about two weeks (caused by the incubation period, reporting delay, accumulation of evidence; Fig. 1 B, C). With the second change point, λ approaches the critical value where the infection rate λ balances the recovery rate μ, i.e. the effective growth rate $\lambda^* = \lambda - \mu \approx 0$ (Fig. 1, orange traces). We currently expect that the third change point brings the effective growth rate into a subcritical regime ($\lambda^* < 0$, Fig. 1 green traces), implying an exponential decrease of novel case numbers.

Our detailed analysis shows that, *in the current phase*, reliable short- and long-term forecasts are very difficult, if not impossible: In Fig. 1C,D the three example scenarios quickly span a huge range of future case numbers. The uncertainty on the short term arises because the magnitude of our social distancing in the past two weeks could not be quantified yet. Beyond two weeks, the case numbers depend on our future behavior, for which we have to make explicit assumptions. We illustrate how the precise magnitude and timing of potential change points impact the forecast of case numbers (see Fig. 4, main paper).

Conclusions. We developed an inference framework to infer the spreading rate λ and the timing and magnitude of change points. Thereby, the efficiency of political and individual measures for social distancing and containment can be assessed in a timely manner. We find first evidence for a successive decrease of the spreading rate in Germany around March 8 and around March 16, which significantly reduced the magnitude of exponential growth, but was not sufficient to turn growth into decay. The development in the coming two weeks will reveal the efficiency of the subsequent social distancing measures. In general, our analysis code may help to infer the efficiency of measures taken in other countries and inform policy makers about tightening, loosening and selecting appropriate rules for containment.

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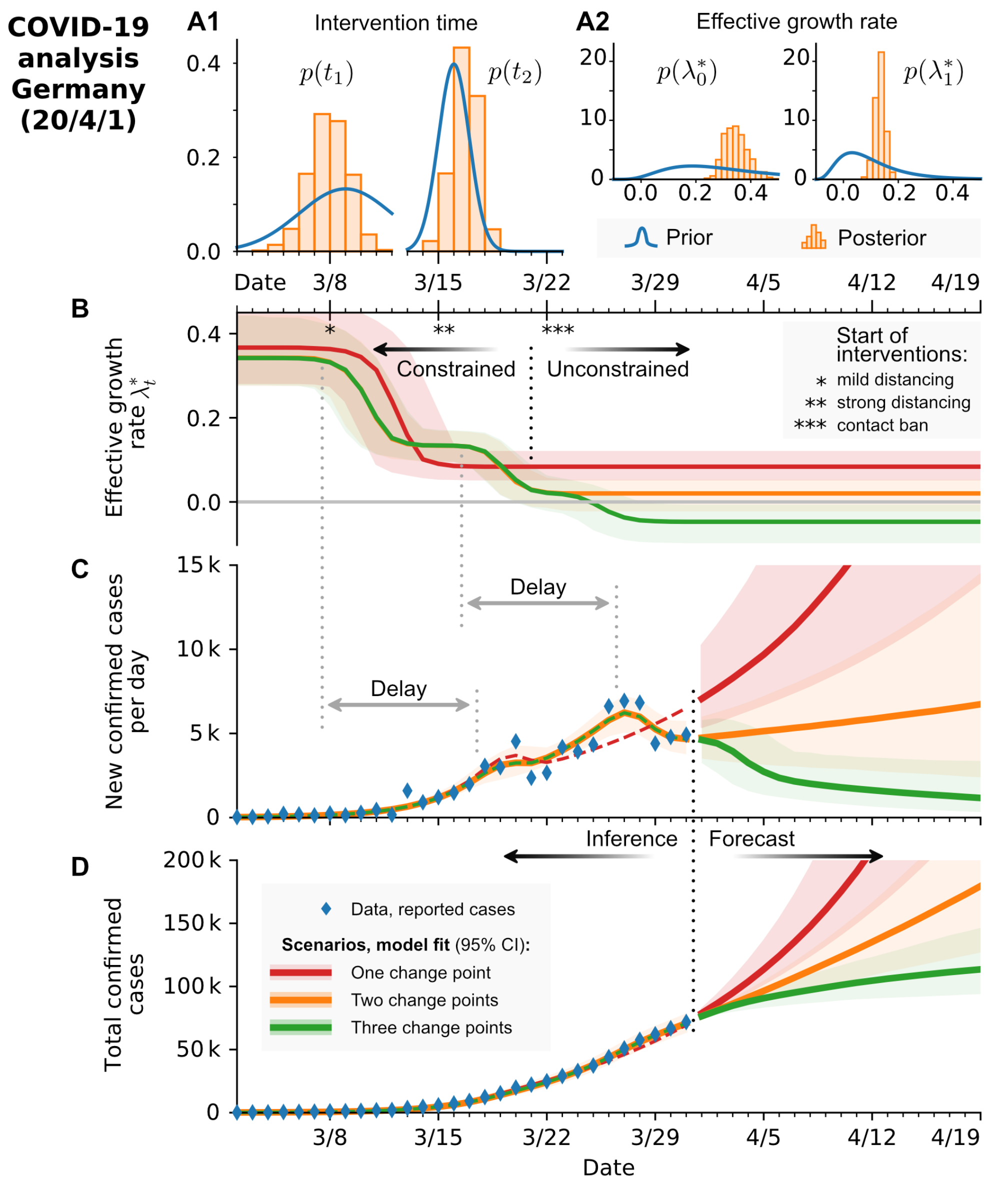

FIG. 1. [This figure uses data available as of April 1st. On our github repository you find the current figure versions.] Inference of spreading rate λ from confirmed COVID-19 cases in Germany, and forecast of future evolution. **A:** Prior (blue) and posterior (orange) distributions for four of the central parameters of a SIR model with two change points (at time t_1 and t_2), where the spreading rate changes from $\lambda_0 \to \lambda_1 \to \lambda_2$. **B:** The inferred effective growth rate λ^*, i.e. the difference between spreading and recovery rate ($\lambda^* = \lambda - \mu$) for an SIR model which assumes one, two or three change points (red, orange, green). The models with two or three change points are favored over the one with one change point by formal Bayesian model comparison. The inferred change points correspond well to the timing of the governmental interventions in Germany (depicted as $*$). **C,D:** The model fit of the new confirmed cases and (cumulative) total confirmed cases is depicted for the models with one, two or three change points. The three future scenarios depend strongly on whether one includes the second or third change point: the number of new confirmed cases will grow exponentially, be approximately constant, or decay exponentially (red, orange, green). Hence, the future development depends predominantly on our behavior. **B,C:** Note the delay D between change point (i.e. change in spreading behavior) and observation of confirmed cases of almost two weeks.

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