Reassessment of New Normal Along with Its Typical Measures Against Covid-19 via an Optimal Decision Framework

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Challenges set by COVID-19 in terms of deadliness, propagation speed, and gained immunity remain unprecedented. As the vaccine production races against virus mutations, international communities are settling toward the new normal guided by local government and health authorities. This study asks how well such transition has been applied in Germany by assessing the functionality of typical measures against the disease. We propose a mathematical model to govern mechanistic processes behind the epidemics. The analysis focuses on to what extent face mask, its efficacy, and community awareness in the likelihood of enhancing physical distancing may significantly suppress the incidence in the long run. Focusing on reemerging peaks of outbreaks during winter season, our sensitivity analysis and optimal decision framework recommend that guaranteeing the locals to uphold physical distancing during the festive season (beginning of November to the end of December) is urgent and effective in reducing the inflow of new cases.

1 Introduction

Promoting health guidelines for combating COVID-19 is a key measure irrespective of educational, social, and economic background of a community. This is useful in two ways as to get rid of misinformation about the disease and to apprise locals of preventive actions such as washing hands, wearing face masks, keeping physical distance, timely reporting and performing RT-PCR tests, compliance to therapeutics etc.[1–3] All these measures should essentially be met amidst the presence of vaccines whose efficacy is still variable over time due

DOI: 10.54103/milanoup.73.71

to advancing virus mutation.[4,5] Three main debilitating variants are identified: B.1.1.7 (UK), B.1.351 (South Africa) and P.1 (USA, Brazil).[6] Germany has also experienced the variant B.1.1.7 according to the Robert Koch Institute.[7] Higher transmission facilitates more variants leaving the vaccine efficacy in danger. Even though some vaccines show promising excesses, for example BNT162b2 (Pfizer/BioNTech) of 95% and mRNA-1273 (Moderna/NIAID) of 94.1% efficacy, achieving ultra-cold storage temperature is problematic.[8] The efficacy of AZD1222 (AstraZeneca/University of Oxford) is reported as 70.4% and Gam-COVID-Vac as 91.6%.[9] These are well above the expectation of WHO, where they prefer 70% efficacy, but with 50% minimum.[10,11] However, efficacy is solely evaluated via clinical trials and hence effectiveness in the community level may differ from the efficacy. Vaccination programs have to be suspended if mutations do not respond to vaccines as experienced in South Africa.[12] On the other hand, until effective vaccination programs are established globally, relaxing mask wearing, physical distancing and hygiene practices may worsen the pandemic situation.[13,14] Willingness to get the vaccine also varies according to socio-economic background.[15] As our main interest, in Germany, a total of roughly 3.5 million primary vaccinations have been administered by February 22, 2021. Starting on December 27, 2020, the average frequency accounted for approximately 58 thousand primary vaccinations per day, with a peak value of 95 thousand per day.[16] Given that a herd immunity is *expected* at a vaccination level of 60–70% of the population, even at the current peak frequency, it would take roughly 500–600 days to achieve, which refer to summer 2022. Hence, the need for a mid- to long-term plan is inevitable.

Our present study subsumes the use of two radical measures, namely face mask and media report, in the context of optimal decision framework applied to an epidemic model. SARS-CoV-2 is usually transmitted through respiratory droplets around 5 μm size, known as aerosols.[17] The commonly used cloth mask is usually of one layer (either of flannel, silk, or chiffon), which for aerosols of size 5 μm, gives efficacy 40% (flannel), 50% (silk), and 70% (chiffon), respectively.[18] At the start of the COVID-19 pandemic, mixed perceptions were evident on wearing face masks. Notwithstanding political and social opinions, now people are aware of the importance of face masks as a self precaution. However, the public level compliance is diverse as some people wear masks just to avoid legal actions rather than following a preventive measure. On top of this, media reporting is also positive endeavor that not only helps encourage mask usage but also makes the state of the art physical distancing and its legal enforcement come to light as the surrounding cases increase. In Germany, physical distancing is usually practiced as staying away about 2 meters against each other.[19] Travel ban, lockdown, and curfew can be considered as extended actions of physical distancing.

2 An Epidemic Model for Covid-19 in Germany

We divide the human population N into six subpopulations based on their health status: susceptible S (healthy but vulnerable to infection), detected I (confirmed active cases, may include asymptomatic and symptomatic type), undetected U (unknown incidence level, *dark figure*, mostly asymptomatic), recovered R, and deceased D. The appearance of pre-symptomatic cases is not considered herein. Imports, migrations, net growth (births and natural deaths) are assumed to have inessential contribution to the rise of the population during the short observation period considered, rendering a constant total population $N = S + I + U + R + D$. The first appearance of the model takes the standard SIR-type including deceased subpopulation

$$S' = \mu(S + I + U + R) - \beta\frac{S(I + \varrho U)}{N} + \nu R - \mu S, \tag{1a}$$

$$I' = \alpha\beta\frac{S(I + \varrho U)}{N} - (\gamma + \mu)I, \tag{1b}$$

$$U' = (1 - \alpha)\beta\frac{S(I + \varrho U)}{N} - (\gamma + \mu)U, \tag{1c}$$

$$R' = \gamma(1 - m)I + \gamma U - (\nu + \mu)R, \tag{1d}$$

$$D' = \gamma m I. \tag{1e}$$

In the preceding model, β denotes the infection rate, $1/\gamma$ the average infection duration, $1/\nu$ the duration of temporary immunity, and m the fatality rate from the detected cases. We impose a strong assumption that the new infected cases are timely distributed into the detected and undetected cases with the proportions α and $1 - \alpha$, respectively. On an effort to accommodate different transmission scales from detected and undetected cases, we use the parameter $\varrho \gg 1$. Moreover, dark figure has largely been unknown, encouraging ideas for proper estimates. Ours is based on the simple consideration that the dark figure proportionates the detected cases to a certain constant, i.e., $U = pI$ for some p. This imposition apparently engenders equivalence of equations (1b) and (1c) under the condition $\alpha = 1/(1 + p)$.

Our model may restrain from legitimate specification due to largely non-observable variables, for example the susceptible S and recovered subpopulation R. To ameliorate this dilemma, we cut down the complexity by assuming proportionality of R to D up to a certain constant or $R \simeq [\tilde{\nu}/(\mu + \nu - \tilde{\nu})] \cdot D$ for some $\tilde{\nu} < \nu$. It thus is expected that $(\mu + \nu)R = \tilde{\nu}(R + D) = \tilde{\nu}[N - S -$

$(1+p)I]$. Avoiding hulking notations, we trace back the original ones through $\beta(1+\varrho p) \mapsto \beta$ and $\tilde{\nu} \mapsto \nu$ such that the model simplifies to

$$S' = \mu(1+p)I - \beta\frac{SI}{N} + \nu[N - S - (1+p)I],$$
$$I' = \frac{\beta}{1+p}\frac{SI}{N} - (\gamma+\mu)I.$$

2.1 Integrating the Use of Face Masks

We are considering the application of cloth masks of average efficacy u. Let $v \in [0, 1]$ be the effective proportion of $S-$ and $I-$individuals who wear masks especially during contact. Infection cases happen accordingly due to contact between: (a) unmasked $S-$ and unmasked $I-$individuals $(1-v)S \cdot (1-v)A$, (b) unmasked $S-$ and masked $I-$individuals with a lack of efficacy $(1-v)S \cdot (1-u)vI$, (c) masked $S-$ and unmasked $I-$individuals $(1-u)vS \cdot (1-v)I$, and (d) masked $S-$ and masked $I-$individuals $(1-u)vS \cdot (1-u)vI$. The proportion terms in the preceding specification sum up to $(1-v)^2 + 2(1-u)v(1-v) + (1-u)^2v^2 = (1-uv)^2$. This transforms the model into

$$S' = \mu(1+p)I - \beta(1-uv)^2\frac{SI}{N} + \nu[N - S - (1+p)I],$$
$$I' = \frac{\beta}{1+p}(1-uv)^2\frac{SI}{N} - (\gamma+\mu)I.$$

Observe that the most ideal situation is prescribed by all $S-$ and $I-$individuals wearing masks during contact ($v = 1$) with a high quality and efficacy 100% ($u = 1$) such that no infection is prevailing.

In what follows, the model will be normalized under the new notations $s := S/N$, $i := I/N$ in order to avoid clash of dimensions as community awareness comes into play.

2.2 Media-Induced Community Awareness

The preceding model neglects the fact that media reports also help shape individual conduct and mindset during epidemics.[20,21] Assessment on the change of community awareness due to media reports have received increasing attention recently. As reviewed in,[22] there are several ways of treating epidemic models to incorporate media reports, depending on which types of feedback induced. Complementary to the face masks is then the role of media reports in educating people around the enhancement of physical distancing in the vicinity of increasing incidence, which ultimately reduce the infection rate β. Which news content is relevant should be addressed appropriately. Here, we center around news related to the number of daily cases and 'how–to' physical distancing, whereas news containing law enforcement on using masks is treated separately by the definition of v. We opt for the ansatz

$$\beta := \beta_0 - (\beta_0 - \beta_1)\frac{i}{\frac{1-w}{w} + i} \tag{2}$$

such that the model transforms into the final version

$$s' = \mu(1+p)i - \left[\beta_0 - (\beta_0 - \beta_1)\frac{i}{\frac{1-w}{w} + i}\right](1-uv)^2 si + \nu[1 - s - (1+p)i], \tag{3a}$$

$$i' = \left[\beta_0 - (\beta_0 - \beta_1)\frac{i}{\frac{1-w}{w} + i}\right]\frac{(1-uv)^2}{1+p} si - (\gamma + \mu)i. \tag{3b}$$

From the formula in (2), $\beta_0 = \beta|_{i=0}$ can be understood as the initial infection rate when first infection is introduced in the 'virgin' (completely susceptible) population. We assume that $\beta_0 > \beta_1$. The fact $\partial_i \beta|_{i=0} \sim -w/(1-w)$ indicates how $w \in [0, 1]$ may portray the interplay between intensiveness of media reports and resulting public awareness. As $w = 1$, the perfect individual awareness casts the largest depression angle of β at the earliest infection. The parameter β_1 can now serve as the saturating infection rate under continuous media reports or perfect awareness, or under overwhelming incidence.

2.3 Reproduction Number

Attention is to be paid when deriving a reproduction number for fleeting observations. It may not be based upon the long-term behavior of the model solution around an equilibrium since the model is not designed to incorporate long-term mechanistic processes that may involve multiple peaks. We are more concerned with the short-term behavior as measured from a point of interest, which in this case is the disease-free equilibrium $(s, i) = (1, 0)$. Analysis of the local behavior of the deviation $(s-1, i)$ around the origin falls into the standard technicality whereby the maximal real part of the eigenvalues of the Jacobian matrix determines the stability.[23] In the present context, the maximal real part is negative providing that the basic reproduction number $\mathscr{R}_0 := \beta_0(1-uv)^2/(1+p)(\gamma+\mu) < 1$. Digressing such an initial direction of endemicity, it is of great interest to see the furtherance of the disease reproduction over time as a response of various events and actions. Symptomatic persons may already draw forth new secondary cases as early as the onset of symptoms, i.e., even before hospital discharge. However, our model (3) did not capture the generation intervals that would have estimated the onsets of symptoms. Following the idea in,[24] in place of $\mathscr{R}_0$ we introduce the *instantaneous* reproduction number

$$\mathscr{R}_t := \left[\beta_0 - (\beta_0 - \beta_1)\frac{i(t)}{\frac{1-w}{w} + i(t)}\right] \cdot \frac{(1-uv)^2}{(1+p)(\gamma+\mu)} \cdot s(t). \tag{4}$$

Observe from (3) that $\mathscr{R}_t$ gives the expected number of secondary cases in S occurring at time instant t attributed to one infected individual per average illness period $1/(\gamma+\mu)$. Under $i(t) > 0$, the checkpoint $\mathscr{R}_t = 1$ is equivalent to $i'(t) = 0$. Therefore, if $i(t)$ speaks about 'order of magnitude', then $\mathscr{R}_t$ gives 'direction of disease progression'. The method in[25] and its smooth variants[26,27] use estimates of the structure of $\mathscr{R}_t$ from compartmental models when data on both daily incidence and (prior density of) generation interval are known.

2.4 What Flattens the Endemic Curve Most Effectively

Let us denote $uv := z$ such that achieving a larger z can be done through making either u or v larger. The key to flattening the endemic curve is scaling down the total number of active cases $\mathcal{I}(z,w) = \int_{t_s}^{t_f} i(t; z, w)\,\mathrm{d}t$, where t_s, t_f denote the starting and final observation. We are asking which parameter between z and w is better in doing this job through the aid of sensitivity analysis. As a means of perturbation, let ε denote the percentage of gain from the current value z (or w), i.e., such that $(z + \varepsilon z)/z = 1 + \varepsilon$ defines the total percentage post increment. In response, $\mathcal{I}$ suffers from the following change in the similar manner

$$\frac{\mathcal{I}(z+\varepsilon z, w)}{\mathcal{I}(z,w)} = 1 + \varepsilon z \frac{\partial_z \mathcal{I}(z,w)}{\mathcal{I}(z,w)} + \mathcal{O}(\varepsilon^2). \tag{5}$$

Typically, the terms $\partial_z\mathcal{I}$ and the non-dimensionalized equivalent $z\partial_z\mathcal{I}/\mathcal{I}$ denote the first-order sensitivity and elasticity, respectively, cf. [28–30] The integrands of the sensitivity indices for all the parameters can be calculated from the linear system

$$\frac{\mathrm{d}}{\mathrm{d}t}\nabla_{(z,w)}\begin{pmatrix} s \\ i \end{pmatrix} = \nabla_{(s,i)}\begin{pmatrix} s' \\ i' \end{pmatrix} \cdot \nabla_{(z,w)}\begin{pmatrix} s \\ i \end{pmatrix} + \nabla_{(z,w)}\begin{pmatrix} s' \\ i' \end{pmatrix}, \quad \nabla_{(z,w)}\begin{pmatrix} s \\ i \end{pmatrix}(0) = 0.$$

In this context, the elasticity denotes the first-order gain percentage (in case positive) or loss percentage of $\mathcal{I}$ (in case negative) from imposing perturbation on z with the gain percentage ε. If one were to measure the sensitivity using the elasticity, then it was with two conditions: the stepping ε was considered the same for all the parameters, and that it is of the first-order stepping. In the present investigation, we are in a good position to know that the role of the

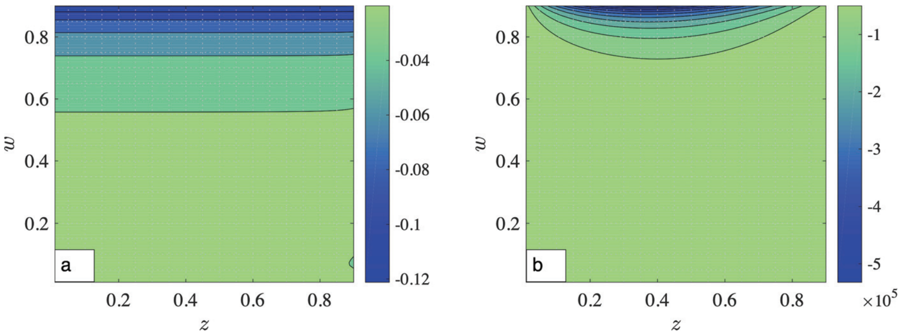

Figure 1: The elasticities $z\partial_z\mathcal{I}(z, w)/\mathcal{I}(z, w)$ in panel (a) and $w\partial_w\mathcal{I}(z, w)/\mathcal{I}(z, w)$ in panel (b) for the parameters in Fig. 2 except where $(z, w) \in [0, 0.91]^2$.

measures z and w is to inhibit the inflow of new cases, therefore it is natural that $\partial_z\mathcal{I}$ and $\partial_w\mathcal{I}$ are always negative. For general models, however, such $\mathcal{I}$ may not be a good measure as it fails to impart the distortion in $\partial_{(z,w)}i$ around zero that eventually sums up to a small number with time.

In Fig. 1, the elasticity corresponding to w takes much larger absolute values than that corresponding to z does. Both elasticities also jump to larger absolute values in the direction of increasing w, but remain essentially constant in the direction of increasing z especially when $w \leq 0.7$. As small as w may be in reality, it is considered the most effective way of attacking the infection rate β. The message being, shaping public perception about the disease and their self-defense system is more important than following mask-usage regulations in a dully manner.

3 Model Fitting

3.1 Known Parameters, Likelihood Function, and Goodness of Fit

In Germany, the use of medical masks has been enforced since January 19, 2021 if one were to use communal facilities.[31] Accordingly, the effective usage as well as efficacy have altered since then. Using the mathematical conventions $\mathbb{T} := \{t_s, t_s + 1, t_s + 2, \cdots, t_f\}$ and $\mathbb{1}_\Omega$ taking value 1 on Ω or otherwise 0, the preceding statement translates to $u = u_1\mathbb{1}_{[t_s,\tau)} + u_2\mathbb{1}_{[\tau,t_f]}$ and $v = v_1\mathbb{1}_{[t_s,\tau)} + v_2\mathbb{1}_{[\tau,t_f]}$ where τ denotes the switch indicating the aforementioned policy change. With such a formulation, an abrupt change is to be expected from $\mathscr{R}_t$ at τ. The average lifespan of the citizens $1/\mu$ and the average illness duration $1/\gamma$ are given by 80 years[32] and 14.3 days for all patients with various treatments,[33] respectively. The Germany's population in 2020 is estimated around 83,950,000.[34] Now, estimation of the unknown parameters $\theta = (s_0, i_0, \beta_0, \beta_1, \nu, p, u_1, u_2, v_1, v_2, w)$ will serve the purpose of finding agreement between model solution $\mu_j := i(t_j)$ and empirical data $\mathscr{I}_j$. With no knowledge on the prior density of θ, the usual workaround is using a likelihood function for its proportionality to the posterior density of θ.[35] The likelihood for a single observation L_j is assumed to be Gaussian with mean μ_j and standard deviation σ. The log of the joint likelihood for the entire observations is $\log \mathcal{L}(\theta) = \log \left(C \prod_j L_j \right)$ where C helps omit the appearing constant before the exponential function, cf.[36] The final representation reads as

$$\log \mathcal{L}(\theta) = -\frac{1}{2} \sum_{j:t_j \in \mathbb{T}} \left(\frac{i(t_j;\theta) - \mathscr{I}_j}{\sigma} \right)^2 . \tag{6}$$

Thanks to σ, its arbitrary value may set the log likelihood in a reasonable order of magnitude for the sake of efficient computations. Our choice was the rescaled mean $\sigma = 10^{-2} \cdot \|\mathscr{I}\|_1/|\mathbb{T}|$.

As the parameter dimension is much smaller than the data size, the *asymptotic confidence interval*[37] has been suggested to describe the parameter uncertainty, which usually is approached by negative of the inverse information matrix. The formula of the confidence interval for each optimal parameter $\hat{\theta}_k$ takes the form

$$\left[\hat{\theta}_k - \varepsilon_k, \hat{\theta}_k + \varepsilon_k\right] \quad \text{where} \quad \varepsilon_k := \sqrt{2\chi^2(\alpha, df) \cdot \left(-\nabla^{-2} \log \mathcal{L}(\hat{\theta})\right)_{kk}}. \tag{7}$$

The operator ∇^{-2} denotes the inverse of the Hessian matrix, while $\chi^2(\alpha, df)$ denotes the α quantile of the χ^2 distribution with the degree of freedom df. In the present study, the Hessian matrix was approximated in the second order using the queen-type stencil, where the step size was made dependent on the parameter's order of magnitude or $\delta_k := \delta \cdot \theta_k$ for a uniformly small δ. The degree of freedom can be chosen between two that further determines the type of confidence interval: $df = 1$ gives *pointwise* asymptotic confidence interval that works on the individual parameter, $df = |\theta|$ gives a *simultaneous* asymptotic confidence interval that works jointly for all the parameters.[38]

3.2 Data and Optimization Solver

The epidemic data for this study are collected from the Johns Hopkins University repository,[39,40] spanning the time window July 1, 2020 until February 20, 2021. We extracted the active cases ($\mathscr{I}$) by subtracting accumulated by recovered and deceased cases.[41] We employ `fmincon` in MATLAB with `interior-point` as the core method to solve the parameter estimation problem. The gradient and Hessian matrix of the negative log likelihood were supplied in separate subroutines so as to speed up the computation. The fitting results can be seen in Fig. 2(a).

θ_k	s_0	i_0	β_0	β_1	ν	p	u_1	u_2	v_1	v_2	w
LB	0.7	$0.1\mathscr{I}_1$	0	0	$\frac{1}{365\cdot 3}$	0	0	0	0	0	0
UB	1	$3\mathscr{I}_1$	1.8	β_0	$\frac{1}{100}$	20	1	1	1	1	1
$\hat{\theta}_k$	0.9999959523	$3.4411 \cdot 10^{-5}$	1.699	$2.982 \cdot 10^{-9}$	0.000913	14.7619	0.0191	0.682	$2.17 \cdot 10^{-10}$	0.28	0.473
$\hat{\varepsilon}_k$	$1.83 \cdot 10^{-5}$	$2.46 \cdot 10^{-8}$	$4.43 \cdot 10^{-4}$	$4.85 \cdot 10^{-10}$	$1.23 \cdot 10^{-6}$	0.0011	$9.74 \cdot 10^{-4}$	0.0915	$1.11 \cdot 10^{-11}$	0.0376	0.0015
$\bar{\varepsilon}_k$	$6.25 \cdot 10^{-4}$	$8.41 \cdot 10^{-7}$	0.0151	$1.65 \cdot 10^{-8}$	$4.19 \cdot 10^{-5}$	0.0359	0.0332	3.1205	$3.77 \cdot 10^{-10}$	1.2832	0.0521

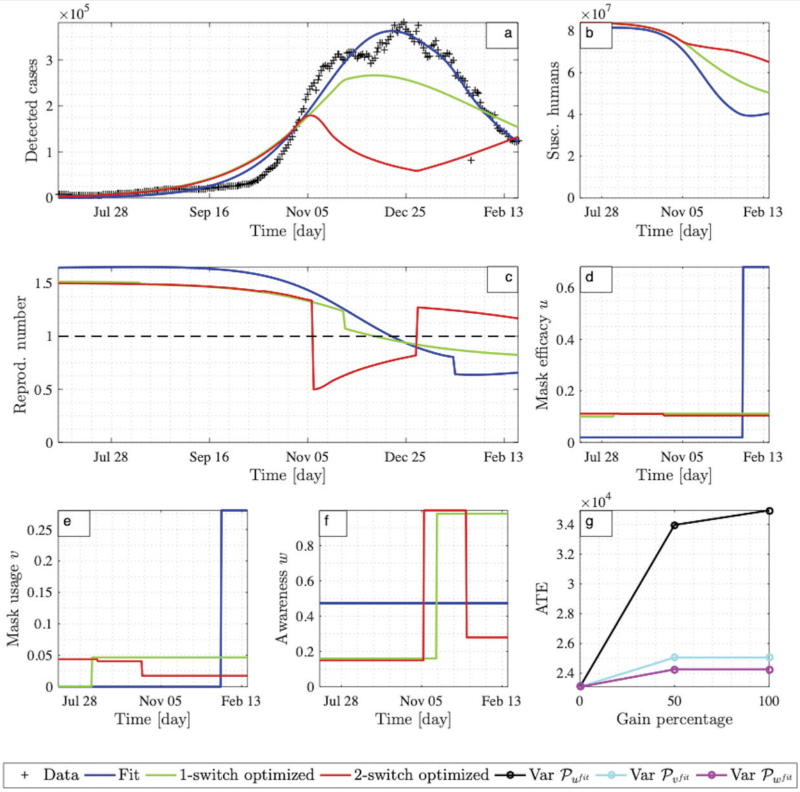

Figure 2: Fitting result with predetermined lower bounds (LB) and upper bounds (UB) for the parameters and the ranges for the confidence intervals with $\hat{\varepsilon}_k := \varepsilon_k(\alpha = 0.05, df = 1)$ and $\bar{\varepsilon}_k := \varepsilon_k(\alpha = 0.05, df = 11)$. The fit-trajectories and those using optimal decision and switching with the number of switches $M = 1, 2$ are shown in panel (a)–(c). The corresponding control measures can be seen in panel (d)–(f). Panel (g) displays different scenarios emanated from ATE if the price for every measure were partially increased in percentage from the current value. The largest yield of ATEs by varying $\mathcal{P}_{u^{\text{fit}}}$ returns from the fact that the measure was not used optimally in the previous optimization due to a small price.

4 Optimal Decision and Switching

The main point of the present investigation is to see what could have been the situation when all the non-vaccine measures were optimized. On the practical level, our model can be used to predict incidence during the next winter season based on a first take-off and may elucidate what to do with the measures in an optimal way. We suppose that switches related to national programmes against COVID-19 could have been assigned more frequently, represented by knot points $\tau_j^u = \tau_j^v$ and τ_j^w for $j = 1, \cdots, M$. The function w depends on the will and political agreement between health authorities and media to disclose information to the public. Meanwhile, the efficacy and effective usage of masks u, v vary from country to country due to the availability of equipment as well as different mentality. Notwithstanding these aspects, too large M may also cause confusion, chaos and lack of compliance to the new regulations.

The control variables can now be formulated as $u = \sum_j u_j \mathbb{1}_{[\tau_j^u, \tau_{j+1}^u)}$, $v = \sum_j v_j \mathbb{1}_{[\tau_j^u, \tau_{j+1}^u)}$, and $w = \sum_j w_j \mathbb{1}_{[\tau_j^w, \tau_{j+1}^w)}$ (with $\tau_0 = t_s$ and $\tau_{M+1} = t_f$) living in the space of functions with bounded total variations and undetermined constants $(\boldsymbol{u}, \boldsymbol{\tau}) = (u_1, \cdots, w_{M+1}, \tau_1^u, \cdots, \tau_M^w) \in [0,1]^{3M+3} \times [t_s, t_f]^{2M}$. To show the power of the method, we calculated the optimal constants toward minimizing the active cases subject to the same 'prices' defined from the fitting $\mathcal{P}_y := \int_{t_s}^{t_f} y \,\mathrm{d}t$ for $y \in \{u^{\text{fit}}, v^{\text{fit}}, w^{\text{fit}}\}$. With the aid of optimal parameters, the problem reads as

$$\min_{(\boldsymbol{u},\boldsymbol{\tau})} \int_{t_s}^{t_f} i^2(t; \boldsymbol{u}, \boldsymbol{\tau}) \,\mathrm{d}t \quad \text{s.t.model(3)and} \int_{t_s}^{t_f} z_y \,\mathrm{d}t \leq \mathcal{P}_y,\ z_y \in \{u, v, w\}, \tag{8}$$

returning $(u^{\text{opt}}, v^{\text{opt}}, w^{\text{opt}})$. Our monitoring function is the *average treatment effect*

$$\text{ATE} := \frac{1}{|\mathbb{T}|} \sum_{j: t_j \in \mathbb{T}} I(t_j; u^{\text{fit}}, v^{\text{fit}}, w^{\text{fit}}) - I(t_j; u^{\text{opt}}, v^{\text{opt}}, w^{\text{opt}})$$

representing how many humans could have been free from infection on a daily basis by the optimal decision and switching.

Using `fmincon`, we were once again able to locate a local minimum to the problem (8) using two tested schemes ($M = 1$ and $M = 2$), as can be seen in Fig. 2. Generally, it is always possible to find optimal values for the measures as well as the switches during winter season. Our local minimum suggests that mask efficacy could have been made moderate but people's discipline toward regularity of the mask usage needs to be improved over all the observations. Focusing on awareness-driven physical distancing during the festive season (beginning of November until end of December) seems to be paramount. According to our model, minimizing the number of actives cases – by maximal ATEs – with the measures u, v, w is equivalent to suppressing the inflow of new cases. It thus is not surprising that the optimal measures return more susceptible humans.

5 Conclusion

This study compares the real-time feedback and an early-warning system with the aid of parameter estimation from an epidemic model, applied to COVID-19 incidence data from Germany. The early warning was brought in the context *as if* the active cases in the next winter season would delineate the same trajectory as for the current winter season. With the full coverage of the season, our model solution easily agrees with the data. We have computed optimal measures focusing on face masks and community awareness apropos of physical distancing, subject to the same prices from the real-time feedback. By prices we do not only narrow-mindedly mean the cost of equipment but also assume all the situations tailored, which can be economical (e.g. loss of jobs, unemployment, healthcare cost) and social (insecurity against others, Work–from–Home). For applicability, we employed the piecewise-constant type of measures whereby switches indicate policy changes. It is generally concluded that a good combination of mask efficacy, regular use of masks, and physical distancing through the aid of media reports or educational campaigns will help reduce the significant inflow of new cases especially from the First Advent Sunday until the end of the Christmastide. Applying physical distancing on the maximum effort during this period critically diminishes the number of active cases.

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