This is the published version of a paper published in .

Citation for the original published paper (version of record):

Bock, W., Jayathunga, Y., Götz, T., Rockenfeller, R. (2021)
Are the upper bounds for new SARS-CoV-2 infections in Germany useful?
*Computational and Mathematical Biophysics*, 9(1): 242-260
https://doi.org/10.1515/cmb-2020-0126

Access to the published version may require subscription.

N.B. When citing this work, cite the original published paper.

Permanent link to this version:
http://urn.kb.se/resolve?urn=urn:nbn:se:lnu:diva-124530
Are the upper bounds for new SARS-CoV-2 infections in Germany useful?

Abstract: At the end of 2019, an outbreak of a new coronavirus, called SARS–CoV–2, was reported in China and later in other parts of the world. First infection reported in Germany by the end of January 2020 and on March 16th, 2020 the federal government announced a partial lockdown in order to mitigate the spread. Since the dynamics of new infections started to slow down, German states started to relax the confinement measures as to May 6th, 2020. As a fall back option, a limit of 50 new infections per 100,000 inhabitants within seven days was introduced for each district in Germany. If a district exceeds this limit, measures to control the spread of the virus should be taken. Based on a multi–patch SEAIRD–type model, we will simulate the effect of choosing a specific upper limit for new infections. We investigate, whether the politically motivated bound is low enough to detect new outbreaks at an early stage. Subsequently, we introduce an optimal control problem to tackle the multi–criteria problem of finding a bound for new infections that is low enough to avoid new outbreaks, which might lead to an overload of the health care system, but is large enough to curb the expected economic losses.

Keywords: COVID–19, Epidemiology, Disease dynamics, SEAIRD–model, Optimal control

MSC: 92D30, 93-10

1 Introduction

Since its first appearance in Wuhan, China, in December 2019, SARS-CoV-2 became a threat worldwide and imposed massive challenges to different societies [1]. The virus as of October 8th 2021, attested in every country, with a total of 237,637,117 detected cases and 4,851,140 associated deaths [2], leading to counter measures worldwide. There are various models predicting massive outbreaks in the case that decision makers do not invoke countermeasures [3, 4, 5].

In the absence of vaccines and reliable pharmaceutical treatment, non–pharmaceutical interventions (NPIs) were established in almost every country and are since the objective of intensive studies [4, 6]. After first infection [7, 8], federal government announced a partial lockdown in order to mitigate the spread [9]. Despite evidence for the efficacy of NPIs, there is growing criticism from the economic point of view due to unemployment, challenges for companies, and a possible threat for the social system. A fall of income by around 70% together with a loss of consumption is discussed [10]. For Germany, a loss in GDP of 10% per week for severe NPIs is forecasted [11]. In rapid succession, out–of–lockdown strategies and dynamical NPI strategies were proposed all around the world [6]. The German government, specifically, imposed upper
bounds for the number of newly infected on the level of districts as a quantitative criterion to assess if a lockdown, including school and shop closure, would be locally necessary [9]. The upper bound was set to 50 new infections per 100,000 inhabitants within seven days on the level of individual German districts (Landkreise), see [12]. Districts in which this bound is passed, should enforce severe NPIs for this particular district, but also provide the possibility for the inhabitants to enter the surroundings for shopping and restaurant visits. In May 2020 the upper limit of 50 newly infected per 100,000 citizens was discussed widely acknowledged among experts as a threshold for backtracking and information capacity in the health departments of the districts, see e.g. [13].

In this article, we use a multi-patch-SEAIRD-type model to evaluate the spread of COVID-19 in the German state of Rhineland-Palatinate with its 36 districts, see [14, 15] for similar models. We use an optimal control problem to find upper and lower bounds for which a lockdown can be invoked or eased in each individual district. Mobility within the districts plays a key role. To introduce mobility into the system, a residence-time-budgeting matrix was computed based on the commuting data of districts [16]. As proposed by the German government, the bounds for all districts are assumed to be equal. For the corresponding cost functional, we penalize (i) the time in lockdown, (ii) the number of switches from and into lockdown, to mimic the negative effects on the economy, as well as (iii) the number of death.

2 Methods

2.1 Study design, source of data and study settings

We used a multi-patch-SEAIRD-model to describe the COVID-19 transmission dynamics under time-dependent NPIs for the districts of the German state Rhineland-Palatinate. Since the German government has invoked a rule for the NPIs valid for all districts of Germany, we assumed that this strategy will be also valid for new upper and lower bounds of the newly infected in one week. Altogether, we made the following assumption for our study:

1. The case data in the districts, obtained by the Johns-Hopkins University, do not deviate too much from the obtained case data on the district level from the reporting point of view.
2. The commuting data of Rhineland-Palatinate [16], represent the mobility within the districts suitably.
3. Workplace situation already has reached pre-pandemic normality.
4. Model parameters can be adopted from a previous parameter analysis study for COVID-19 [18], which had been based on time series for Germany. 5) Data on age and comorbidities could be neglected for this study.

It is shown that the age structure plays a huge role in the COVID-19 pandemic, see e.g. [17]. On Landkreis level with the incidences considered in this article however, age stratified data leads to very small compartments, leading to a bad model performance [20]. An agent-based or random graph approach would be of interest in this situation, as in [3, 4]. This on the other hand would make the optimization procedure more involved.

2.2 Modelling NPIs

We considered two different transmission scenarios, namely inner and outer household transmissions. While the transmission within household is hardly preventable, NPIs can lead to a significant reduction of the outer household contacts and hence reduce the outer-household transmissions [3]. In SIR models, this effect can be achieved by reducing the basic reproduction number, see e.g. [6, 19, 20]. For an uncontrolled spread of COVID-19, a reproduction number around 2.6 was found, while post-intervention studies showed a value of 0.62 for certain European countries [20], which corresponds to a reduction of 74.5%. In particular in Germany has a reproduction number of 2.2, which was deduced from data in [18]. With no detailed intervention scheme available, we modelled this effect by the transmission rate. The period in which the NPIs should be
valid in each district were obtained by solving an optimal control problem, in which the absolute time of the lockdown, the deaths from COVID-19 and the number of switches to lockdown and back within a period of 200 days were penalized. This switching represents the economical challenge for a district, to implement these interventions: weekly on-off strategies, with changing measures on a short-term basis are certainly not desirable. The period of 200 days was chosen to have a time horizon which is long enough to see more than one phase of lockdown.

2.3 Multi–Patch–SEAIRD–type model for the regional spread of COVID-19

The mathematical model, which was used throughout this paper constitutes an extension of the model from [18], including the spatial spread of the disease due to movements within the population. This model is a compartmental model of ordinary differential equations in which the total population is divided into six compartments, namely: Susceptible $S_i$, Exposed $E_i$, Asymptomatic $A_i$, Infected $I_i$, Recovered $R_i$ and Deceased $D_i$, where the index corresponds to the specific patch $i$. The state of Rhineland–Palatinate, with a total population of about 4 million inhabitants, is divided into 24 districts and 12 independent cities, see the figure in the supplement. Hence, we considered a total of 36 different patches (district or city) and end up with the 216–dimensional ODE–system:

$$S'_i = -\beta_i(t) \frac{S_i}{N_i} (\rho I_i + \sum_j m_{ij} A_j)$$

$$E'_i = \beta_i(t) \frac{S_i}{N_i} (\rho I_i + \sum_j m_{ij} A_j) - \kappa E_i$$

$$A'_i = \kappa \alpha E_i - \gamma_A A_i$$

$$I'_i = \kappa (1-\alpha) E_i - \gamma_I I_i$$

$$R'_i = \gamma_A A_i + \gamma_I (1-\mu) I_i$$

$$D'_i = \gamma_I \mu I_i.$$  

Here $\beta_i(t)$ denotes the time-dependent transmission rate in patch $i$; due to possible reinforcement of restrictions within individual patches, the transmission rate can vary in time and between districts. Hence, the transmission rate in district $i$ was assumed to contain the following three components:

1. A multiplicative factor $u_i(t) \in (0, 2, 1]$, modelling the control via restrictions to public and economic life. The unrestricted case corresponds to $u_i = 1$ with smaller values of $u_i$ representing more severe restrictions.

2. A base value $\beta_i^0$, representing an average transmission rate within the patch. In this number particularly the inner-household transmission is encoded.

3. A uniform distributed centered random variable $\hat{\beta}_i \in [-0.2, 0.2]$, allowing to capture random fluctuations of ±20% of the outbreaks in different districts.

Summarizing, the transmission rate writes as

$$\beta_i(t) := u_i(t) \cdot \beta_i^0 \cdot (1 + \hat{\beta}_i(t)).$$  

Remark: In this model we have no distinction between detected and undetected cases, i.e. the effect of quarantine is neglected. Indeed detected case if quarantined are not spreading the disease anymore and hence ease the epidemic situation, see [22, 23].

The mobility of healthy and asymptomatic infected people, who are often not even aware of being infectious, is described by a so-called residence-budgeting-time matrix $M = (m_{ij})$. It is important to note that $\sum_{j=1}^{n} m_{ij} = 1$, where $m_{ij} \in [0, 1]$. The coefficient $m_{ij}$ to the fraction of time the population of patch $i$ spent in patch $j$[24]. Based on the commuting matrix[16], which is provided by the government of Germany, the average number of people commuting from one district to another for work is depicts. The matrix $M$ can be deduced, by assuming that an individual spends 1/3 of the day at work (at the state it commutes to if not
working in its residing state) and 2/3 of the day in its residing state. For symptomatic infected, we assume no mobility. The incubation period equals 1/κ and α denotes the fraction of infected being asymptomatic. Recovery periods for asymptomatic and symptomatic equal 1/γ_A ≤ 1/γ_I and finally μ denotes the death rate for symptomatic cases. For asymptomatic cases, lethality is neglected.

The target variables \(Z_i\) of the model represent the new infections per 100,000 inhabitants during the last seven days within a district. This observable had been defined by the German government. Computing the number of new infections for a time span of 7 days, we obtain

\[
Z_i(t) := \frac{10^5}{N_i} \int_0^7 \kappa E_i(t - s) \, ds, \quad \text{where } N_i \text{ is the population of patch } i.
\]

We embedded the question of meaningful upper bounds for new infections into an optimal control framework. The state-wide upper bounds \(Z_{\text{max}}\) and \(Z_{\text{min}}\) serve as the optimization variables to be determined. If the target variable \(Z_i\) in a district exceeds the bound \(Z_{\text{max}}\), a re-implementation of restrictions in the given district is invoked. These restrictions are relaxed again if the target variable drops below a lower bound \(Z_{\text{min}}\). The two bounds \(Z_{\text{max}}\) and \(Z_{\text{min}}\) which were assumed to be constants for every state, serve as the optimization variables to be determined.

For the multiplicative factor \(v_i(t)\), controlling the transmission rate, we obtain \(u_i(t) = 1 - v_i(t)(1 - u_{\text{lock}})\), where \(u_{\text{lock}} < 1\) denotes the reduction of \(\hat{β}\), i.e. the random fluctuations, due to restrictions. The indicator \(v_i(t)\) switches between 0 (no measures) and 1 (lockdown)

\[
v_i(t) = v_i(t - 1) + \begin{cases} 1 & \text{if } v_i(t - 1) = 0 \text{ and } Z_i(t) > Z_{\text{max}} \\ 0 & \text{if } v_i(t - 1) = 0 \text{ and } Z_i(t) < Z_{\text{min}}. \end{cases}
\]

Indeed the model assumes an immediate switching of the control measures as soon as critical thresholds are reached. In practice there may be a time delay, due to the communication and invoking of the countermeasures, which would let the curves grow over the threshold and even make peaks higher until control is undertaken. For the sake of simplicity this is not considered here.

Here, we assumed that reimposed restrictions lead to an 80% reduction of the transmission. This corresponds to a slightly stricter reduction as found in [20].

The objective of the control problem takes three aspects into account

1. The economic loss due to reimposed restrictions. According to [11] the shutdown costs per month account for approximately 400% of the gross domestic product, i.e. 10% per week.
2. The number of fatalities, \(D_i\).
3. The number of switches, \(Q_i\), into the shutdown, since it can be expected that there is an economic loss by imposing the measures within the district, thus making a continuous on-off strategy not feasible.

Hence, we propose the following cost functional as objective of the minimization problem

\[
J(Z_{\text{max}}) = \sum_{i=1}^M \left( \omega_1 \int_0^T N_i \chi(Z_i(t) > Z_{\text{max}}) \, dt + \omega_2 \int_0^T D_i^2(t) \, dt + \omega_3 \sum_{i=1}^M Q_i \, dt \right)
\]

### Table 1: Parameter values of model (1) taken from [18].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\rho)</td>
<td>0.1</td>
<td>–</td>
<td>fraction of infected having contact</td>
</tr>
<tr>
<td>(\kappa)</td>
<td>1/3</td>
<td>1/day</td>
<td>reciprocal incubation period</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>0.3</td>
<td>–</td>
<td>rate to be asymptomatic</td>
</tr>
<tr>
<td>(\gamma_A)</td>
<td>1/10</td>
<td>1/day</td>
<td>recovery rate of asymptomatic cases</td>
</tr>
<tr>
<td>(\gamma_I)</td>
<td>1/14</td>
<td>1/day</td>
<td>recovery rate of symptomatic cases</td>
</tr>
<tr>
<td>(\mu)</td>
<td>0.02</td>
<td>–</td>
<td>death rate for symptomatic cases</td>
</tr>
</tbody>
</table>
where $\chi$ denotes the characteristic function, i.e. $\chi(Z_i(t) > Z_{\text{max}}) = 1$, if $Z_i(t) > Z_{\text{max}}$ and zero otherwise. The weights are set to $\omega_1 = 1000$, $\omega_2 = 1$ and $\omega_3 = 5$ in order to balance the different terms in the cost functional.

For the simulation of system (1), we used a standard explicit Euler method [21]. The optimal control problem, i.e. the search for optimal parameters $Z_{\text{min}}$ and $Z_{\text{max}}$ as lower and upper bounds for the target variable $Z$, was solved with the built-in MATLAB-routine `fminsearch`. Note that the existence of a minimizer is ensured due to the convexity of the cost functional as a sum of convex functions. Note especially that all functions are strictly positive and hence coincide with their absolute values.

The time-dependent transmission rate is a random variable, which has to be taken into account when comparing the cost functional for different parameters $Z_{\text{min}}$ and $Z_{\text{max}}$. For this purpose, a static random seed of 1000 sample paths of $\hat{\beta}_i$, individually for every district, was used. This seed was also used when comparing scenarios with and without the influence of mobility, wherein the latter the residence-time-budgeting matrix corresponds to the identity.

Figure 1 displays the dependence of the weighted duration of restrictions and the number of deaths in Rhineland-Palatinate as a function of the upper bound $Z_{\text{max}}$ of new infections within 200 days and for different lower bounds $Z_{\text{min}}$.

As expected, the total number of man-days in lockdown, summed up over all districts, is monotonically decreasing with growing $Z_{\text{max}}$ for all values of $Z_{\text{min}}$. Note that small oscillations occur due to the time restriction of the simulation, which was chosen to be 200 days. Naturally, the duration of the restrictions increases with larger intervals between the upper and lower bound. The number of deaths is increasing with growing $Z_{\text{max}}$ and growing $Z_{\text{min}}$ respectively. One can clearly see the non-linear behaviour in both curves.

### 2.4 Demographic characteristics and data of COVID-19 cases

Table 2 in the Appendix presents the population size, case numbers, recovered inhabitants and the death numbers for each district in Rhineland-Palatinate as of July 6, 2020. We assume a dark figure of active cases which is equal to the tested active cases and add 10% are asymptomatic and 10% are exposed cases as initial conditions. Since at the time of the study 37% of the total ICU beds in Germany were free, see [7] (12065 free ICU beds for 305 COVID-19 patients with intensive care), the capacity of the health care system in the districts is neglected.
3 Results

3.1 Simulation and predicted optimal intervention strategy

3.1.1 Disease dynamics

In case of no control being imposed, there will be outbreaks in the districts leading to 6708 deaths per 100,000 within the time horizon of 200 days. Mobility plays a role at the beginning of the spreading. Figure 3 and 2 show the disease progression in 4 different characteristic districts, once with and once without mobility between the districts. The $R_0$-value throughout the simulation in the non-controlled phase was 2.2, which is in accordance with previous findings [18]. Note that in this scenario, the initial conditions are based on the current data, i.e. there are cases in different districts already. The mobility hence accelerates the spreading. In Neuwied in Figure 2 infections occur, due to the fact that the district is disease-free. The imports of infections from other districts lead to a later outbreak in Neuwied compared to the other districts displayed. One can see one more effect of the mobility in Figure 3 in the case of Neuwied. The number of infections in the uncontrolled setting coincides well with the infections in the controlled setting for the districts Mainz, Germersheim and Kaiserslautern. For the case of Neuwied both graphs differ slightly. This is due to the fact that the control of the other districts also plays a role on the disease progression of Neuwied in a scenario where mobility is concerned.

![Graphs showing disease progression]

**Figure 2:** Controlled ($Z_c$) and uncontrolled ($Z_{nc}$) disease progression for four districts of Rhineland-Palatinate including mobility between the districts, with $Z_{\text{min}} = 4$ and $Z_{\text{max}} = 100$. 

3.1.2 Optimal bounds for the number of newly infected per week

Based on our model, we formulated an optimal control problem where the number of death, the time of restrictions and the number of switches from a non-NPIs to an NPIs regime is minimized subject to the underlying multi-patch system. The time of the restrictions here was weighted with the population of the district to incorporate the economical importance of the district within the state. Based on 1000 random samples, the lower and upper bounds were optimized w.r.t. the mean of the above costs, using fminsearch. As optimal upper and lower bounds, we found $Z_{\text{max}} = 100$ and $Z_{\text{min}} = 4$. A sample path of $Z$ with these values is displayed in Figure 4. We see that indeed the number of infected can effectively controlled by the NPIs. In [25] a similar concept was used to obtain intervals for NPIs and wave breakers for the second wave based on the seven days incidence. The threshold values there were $Z_{\text{max}} = 50$ and $Z_{\text{min}} = 4$, which is exactly the half of our observations. A reason for this is first that in the considered time span of this article the incidences were relatively low compared to those in autumn. Moreover age-structure has not been considered here, which also may enhance the incidences. Another cause of the deviation is the fact that Rhineland-Palatinate is consisting of low populated areas with few bigger cities. The study of Barbarossa and Fuhrmann [25] was based on the data for whole Germany. In the whole country of Germany dynamics from imports, e.g. from Eastern Europe in the second wave, added significantly to the epidemics. In Rhineland-Palatinate in the considered time frame imports were negligible.

Overall, mobility here had only a minor contribution to the COVID-19 spread. Without mobility, there are few districts with no active disease cases at day 0 and thus no control is needed over the full-time horizon. Including mobility, these districts can become infected by imports and control measures, i.e. NPIs, have to be taken. However in districts where there were already infected cases at the initial time, the mobility results just in a slight time delay in the time series of the infected, since infected are also spending a larger amount of tie outside the patch. Figure 5 illustrates the multiplicative factor $u_i(t)$, controlling the transmission rate over the time considered with the two scenarios including and excluding mobility effect. There are several counties such as Frankenthal (Pfalz) kr.fr. St. and Landau in der Pfalz kr.fr. St. in which the control is not switching over time as the number of newly infected over a 7 days time span is not exceeding the upper limit during the considered 200 days, see Fig. 5. All the other counties are having a switch once or two times during the considered time span accordingly to the number of newly infected over a 7 days time. For disease-free districts
Figure 4: Number of newly infected per 100,000 inhabitants over a 7 days timespan with controlled disease progression for $Z_{\text{max}} = 100$ and $Z_{\text{min}} = 4$.

Figure 5: Time dependent control for for $Z_{\text{max}} = 100$ and $Z_{\text{min}} = 4$. 
such as e.g. Neuwied and Trier kr.fr. Stadt a lockdown is just invoked in the case of mobility and at a very late timepoint.

Note: More simulation results for different lockdown transmission rates and for simulations with and without mobility can be found in the supplementary material. While Figure 5 shows the time dependent control for the scenario with and without mobility, in the supplementary material it is depicted how the dynamics of symptomatic and asymptomatic infected is reacting on this control, compared for the case with and without mobility. The simulation with no control shows the exponential growth of incidences in the districts.

4 Discussion

In this study, we used a multi-patch-SEAIRD-type model with an optimal control problem to deduce optimal bounds for the minimal and maximal number of new infections per week, in order to ease or invoke NPIs as countermeasures for the COVID-19 spreading. The optimal values were computed based on the disease dynamics in the 36 districts of the German state Rhineland-Palatinate. To include random changes in the contacts and to obtain robustness, we perturbed the transmission rate with a uniformly distributed random variable and performed the optimization over a fixed seed of 1000 random samples of the transmission rate.

Our study has several findings. First, we showed that the mobility between the districts plays a minor role if the disease is already spread in the whole state. However, disease-free districts can become infected due to imports. Second, comparing the controlled and the non-controlled scenarios, a small number of NPI phases, which last around 40 days, lead to effective control of the disease progression. The amount of newly infected in 100,000 per week is strictly higher than the 50 suggested by the German government. The lower bound is also strictly larger than 0. Note that quantitatively the number is of course related to the weights set in the optimization problem. For the weights in our scenario the control is realizable and the disease can effectively be kept under control with at maximum 2 lockdowns in 200 days. Compared to the scenario in 2020, this is in a good agreement with the timespan of the lockdowns on March 16th, 2020 and November 2, 2020, which was 231 days.

We assumed here the dark figure of active infected cases to be as high as the number of detected cases, i.e. the number of infected at the beginning of the simulation is really able to contribute to new infections. The number in Table 2 reflects however the detected cases are under quarantine and are hence not infecting other susceptibles. Backtracking and effective testing, together with household quarantine, can, of course, influence our result positively. Thus, our study can be seen as a conservative estimate. We neglected many heterogeneities in the population and omitted super-spreading events, which can, of course, influence the results. Our study may have important implications since we displayed findings relevant for decision-makers in the fight against COVID-19. We provide a strategy that can be easily adapted and used to control the disease progression in Rhineland-Palatinate effectively. The measures can be seen as dynamic since they are adapted to the number of cases in the districts and hence work adaptive to their specific economic needs and also the needs of the whole state. Further, the findings stimulate further research such as the influence of the household structure, which seems crucial for the progression [3], the influence of reduced mobility, i.e. is it really necessary to shield a district completely if the case numbers are not yet high. The influence of basic patient data such as comorbidities, hospitalization rate and the influence of testing and backtracking will certainly lead to more realistic results.

List of abbreviations

GDP: Gross domestic product ICU: Intensive care units NPI: Non pharmaceutical interventions RLP: Rhineland-Palatinate
Availability of data and material: The data is openly available and the sources can be found in the references.

Competing interests: The authors declare to have no significant competing financial, professional, or personal interests that might have influenced the performance or presentation of the work described in this manuscript.

Funding: There was no funding of this project.

Authors’ contributions: W. Bock was involved in modelling and writing. Y. Jayathunga was involved in simulation. T. Götz was involved in modelling and writing. R. Rockenfeller was involved in data collection and writing.

Acknowledgements: We thank an anonymous referee for very constructive comments which improved the article.

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[16] Statistisches Bundesamt, Penderlatlas
https://statistik.arbeitsagentur.de/
A Demographic and disease status of the districts of Rhineland-Palatinate

Table 2: The data source for the population is the Statistisches Bundesamt Deutschland. The data source for the number of cases is Robert-Koch-Institut (RKI), Berlin. The number of cases, recovered and death data areas as of July 6, 2020.

<table>
<thead>
<tr>
<th>District (Nj)</th>
<th>Population</th>
<th>Cases</th>
<th>Recovered</th>
<th>Death</th>
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<tr>
<td>Koblenz kr. fr. St.</td>
<td>114024</td>
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<td>246</td>
<td>18</td>
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<td>159</td>
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B Supplementary figures
Figure 7: Simulation with no control ($\varphi_{lock} = 1$): Infected cases with and without mobility over time in the 36 counties of RLP. The results are scaled to 100,000 inhabitants per county.
Are the upper bounds for new SARS-CoV-2 infections in Germany useful?

Figure 8: Simulation with control ($\mu_{lock} = 0.2$): Asymptomatic cases with and without mobility over time in the 36 counties of RLP. The results are scaled to 100,000 inhabitants per county.
Figure 9: Simulation with no control ($\mu_{lock} = 1$): Asymptomatic cases with and without mobility over time in the 36 counties of RLP. The results are scaled to 100,000 inhabitants per county.
Figure 10: Simulation with no control \((u_{lock} = 1)\) and with mobility: New cases in the past 7 days per 100,000 inhabitants in the 36 counties of RLP.
Figure 11: Simulation with no control ($\mu_{lock} = 1$) and with mobility: New cases in the past 7 days per 100,000 inhabitants over time in the 36 counties of RLP with mobility.
Figure 12: Simulation with control ($u_{lock} = 0.2$) and with no mobility: New cases in the past 7 days per 100,000 inhabitants over time in the 36 counties of RLP with mobility.
Figure 13: Simulation with no control (\(u_{lock} = 1\)) and with no mobility: New cases in the past 7 days per 100,000 inhabitants over time in the 36 counties of RLP with mobility.