The Effectiveness of Strategies to Contain SARS-CoV-2: Testing, Vaccinations, and NPIs *

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In order to slow the spread of the CoViD-19 pandemic, governments around the world have enacted a wide set of policies limiting the transmission of the disease. Initially, these focused on non-pharmaceutical interventions; more recently, vaccinations and large-scale rapid testing have started to play a major role. The objective of this study is to explain the quantitative effects of these policies on determining the course of the pandemic, allowing for factors like seasonality or virus strains with different transmission profiles. To do so, the study develops an agent-based simulation model, which is estimated using data for the second and the third wave of the CoViD-19 pandemic in Germany. The paper finds that during a period where vaccination rates rose from 5% to 40%, rapid testing had the largest effect on reducing infection numbers. Frequent large-scale rapid testing should remain part of strategies to contain CoViD-19; it can substitute for many non-pharmaceutical interventions that come at a much larger cost to individuals, society, and the economy.

JEL Classification: C63, I18
Keywords: CoViD-19, agent based simulation model, rapid testing, non-pharmaceutical interventions

[Tobias 1]
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Since early 2020, the CoViD-19 pandemic has presented an enormous challenge to humanity on many dimensions. The development of highly effective vaccines holds the promise of containment in the medium term. However, most countries find themselves many months—and often years—away from reaching vaccination-induced herd immunity (Swaminathan, 2021). In the meantime, it is of utmost importance to employ an effective mix of strategies for containing the virus. The most frequent initial response was a set of non-pharmaceutical interventions (NPIs) to reduce contacts between individuals. While this has allowed some countries to sustain equilibria with very low infection numbers,[1] most have seen large fluctuations of infection rates over time. Containment measures have become increasingly diverse and now include rapid testing, more nuanced NPIs, and contact tracing. Neither these policies' effect nor the influence of seasonal patterns or of more infectious virus strains are well understood in quantitative terms.

[Janos 1]

Put stronger focus on time dependent rapid test sensitivity (30% before day of onset of infectiousness)

[HM 1]

Need to find some more scientific citation before submission

[Klara 1]

feedback from Philipp:

- he would suggest to lay more focus on explaining the mechanisms behind our results
- he suggests we should try to get some form of confidence bands or standard errors
- he got the wrong impression that we only have three mechanisms and that the rapid tests are the residual.

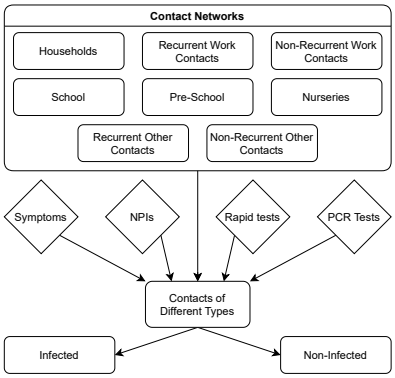
This paper develops a quantitative model incorporating these factors simultaneously. The framework allows to combine a wide variety of data and mechanisms in a timely fashion, making it useful to predict the effects of various interventions. We apply the model to Germany, where new infections fell by almost 80% during the month of May 2021. Our analysis shows that, aside from seasonality, frequent and large-scale rapid testing caused the bulk of this decrease, which is in line with prior predictions (Mina and Andersen, 2021). We conclude that it should have a large role for at least as long as vaccinations have not been offered to an entire population.

At the core of our agent-based model are physical contacts between heterogeneous agents (Figure 1a).[2] Each contact between an infectious individual and somebody susceptible to the disease bears the risk of transmitting the virus. Contacts occur in up to four networks: Within the household, at work, at school, or in other settings (leisure activities, grocery shopping, medical appointments, etc.). Some contacts recur regularly, others occur at random. Empirical applications can take the population and household structure from census data and the network-specific frequencies of contacts from diary data measuring contacts before the pandemic (e.g. Mossong, Hens, Jit, Beutels, Auranen, et al., 2008; Hoang, Coletti, Melegaro, Wallinga, Grijalva, et al., 2019). Within each network, meeting frequencies depend on age and geographical location (see Supplementary Material Section A.3).

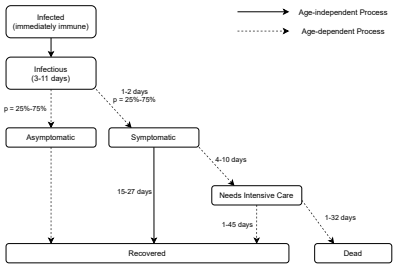
The four contact networks are chosen so that the most common NPIs can be modeled in great detail. NPIs affect the number of contacts or the risk of transmitting the disease upon having physical contact. The effect of different NPIs will generally vary across contact types. For example, a mandate to work from home will reduce the number of work contacts to zero for a fraction of the working population.

1. See Contreras, Dehning, Mohr, Bauer, Spitzner, et al. (2021) for a theoretical equilibrium at low case numbers which is sustained with test-trace-and-isolate policies.

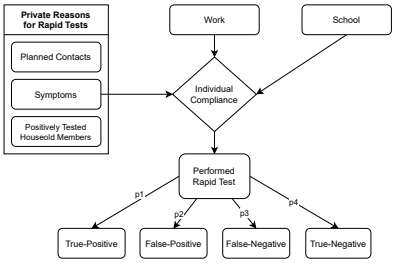
2. A detailed comparison with other approaches is relegated to Supplementary Material B.1. The model most closely related to ours is described in Hinch, Probert, Nurtay, Kendall, Wymatt, et al. (2020).



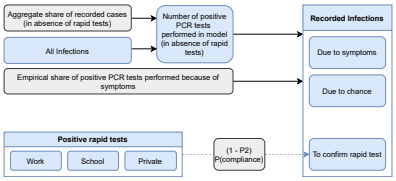
(a) Model for contacts and infections



(b) Disease progression



(c) Model for rapid tests



(d) Translating all infections to recorded ones

Figure 1. Model description

Note: Adescription of the model can be found in Supplementary Material B. Figure 1a shows the influence on an agent's contacts to other agents. Demographic characteristics set the baseline number of contacts in different networks. She may reduce the number of contacts due to NPIs, showing symptoms, or testing positively for SARS-CoV-2. Infections may occur when a susceptible agent meets an infectious agent; the probability depends on the type of contact, on seasonality, and on NPIs. If infected, the infection progresses as depicted in Figure 1b. If rapid tests are available, agents' demand is modeled as in Figure 1c. All reasons trigger a test only for a fraction of individuals depending on an individual compliance parameter; the thresholds for triggering test demand differ across reasons and they may depend on calendar time. Figure 1d shows the model of translating all infections in the simulated data to age-specific recorded infections. The model uses data on the aggregate share of recorded cases, on the share of positive PCR tests triggered by symptoms, and on the false positive rate of rapid tests. The lower part of the graph is relevant only for periods where rapid tests are available.

Schools and daycare can be closed entirely, operate at reduced capacity—including an alternating schedule—, or implement mitigation measures like masking requirements or air filters (Lessler, Grabowski, Grantz, Badillo-Goicoechea, Metcalf, et al., 2021). Curfews may reduce the number of contacts in non-work/non-school/non-work settings. In any setting, measures like masking requirements would reduce the probability of infection associated with a contact (Cheng, Ma, Witt, Rapp, Wild, et al., 2021).

In the model, susceptibility to contracting the SARS-CoV-2 virus is dependent on age. A possible infection progresses as shown in Figure 1b. We differentiate between an initial period of infection without being infectious or showing symptoms, being

infectious (presymptomatic or asymptomatic), showing symptoms, requiring intensive care, and recovery or death (similar to Grimm, Mengel, and Schmidt, 2021). The probabilities of transitioning between these states depend on age; their duration is random within intervals calibrated to medical literature (for a detailed description see Section A.1). Conditional on the type of contact, infectiousness is independent of age (Jones, Biele, Mühlemann, Veith, Schneider, et al., 2021).

[HM 2]
Need to look for non-economists

The model includes several other features, which are crucial to describe the evolution of the pandemic in 2020-2021. New virus strains with different profiles regarding infectiousness can be introduced. Agents may receive a vaccination. With a probability of 75% (Hunter and Brainard, 2021), vaccinated agents become immune and they do not transmit the virus (Levine-Tiefenbrun, Yelin, Katz, Herzel, Golan, et al., 2021; Petter, Mor, Zuckerman, Oz-Levi, Younger, et al., 2021; Pritchard, Matthews, Stoesser, Eyre, Gethings, et al., 2021).[3] During the vaccine roll-out, priority may depend on age and occupation.

We include two types of tests. Polymerase chain reaction (PCR) tests reveal whether an individual is infected or not; there is no uncertainty to the result. PCR tests require some days to be processed and there are aggregate capacity constraints throughout. In contrast, rapid antigen tests yield immediate results; after a phase-in period, all tests that are demanded will be performed. Specificity and sensitivity of these tests is set according to data analyzed in Brümmer, Katzenschlager, Gaeddert, Erdmann, Schmitz, et al. (2021) and Smith, Gibson, Martinez, Ke, Mirza, et al. (2021); sensitivity depends on the timing of the test relative to the onset of infectiousness. Figure 1c shows our model for rapid test demand. Schools may require staff and students to be tested regularly. Rapid tests may be offered by employers to on-site workers. Individuals may demand tests for private reasons, which include having plans to meet other people, showing symptoms of CoViD-19, and because a household member tested positively for the virus. We endow each agent with an individual compliance parameter. This parameter determines whether she takes up rapid tests.[4]

Modelling a population of agents according to actual demographic characteristics means that we can use a wide array of data to identify and estimate the model's many parameters.[5] Contact diaries yield pre-pandemic distributions of contacts for different contact types and their assortativity by age group. Mobility data is used to model the evolution of work contacts. School and daycare policies can be incor-

3. 75% is lower than what is usually reported for after the second dose of the Biontech/Pfizer vaccine, which is most commonly used in Germany. We choose it because our model neither includes booster shots, nor does it allow vaccinated individuals who became immune to transmit the disease(Levine-Tiefenbrun et al., 2021; Petter et al., 2021; Pritchard et al., 2021). If anything, these assumptions would overstate the effect of vaccines for our study period. This would be different if a large fraction of vaccinated individuals had received a second dose already.

4. A positive test result (of either kind), as well as symptoms leads most individuals to reduce their contacts; this is why tests impact the actual contacts in Figure 1.

5. See section A of the supplementary materials for an overview.

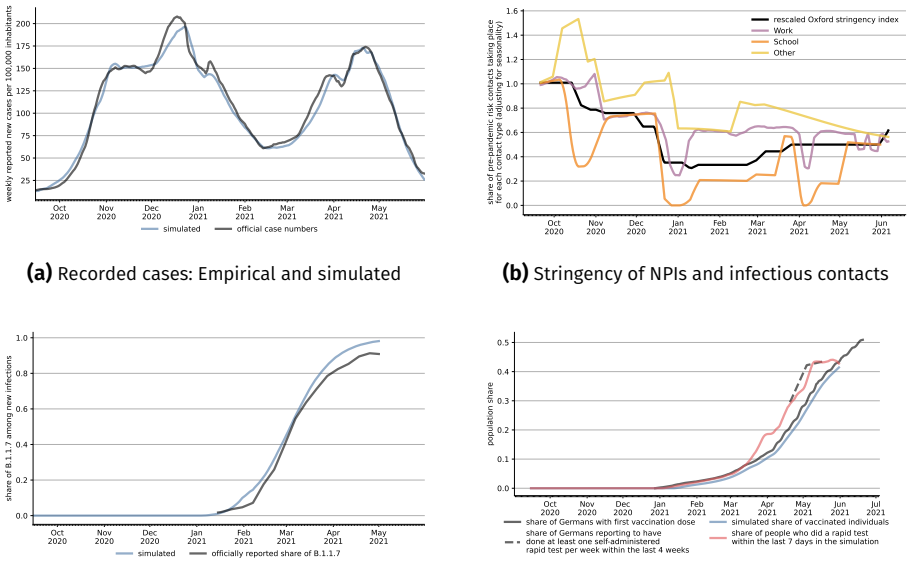
porated directly from official directives. Administrative records on the number of tests, vaccinations by age and region, and the prevalence of virus strains are generally available. Surveys may ask about test offers, propensities to take them up, and past tests. Other studies' estimates of the seasonality of infections can be incorporated directly. The remaining parameters—most notably, these include infection probabilities by contact network and the effects of NPIs, see Supplementary Material B.10—will be chosen numerically so that the model matches features of the data (see McFadden, 1989, for the general method, also described in Supplementary Material B). In our application, we keep the number of free parameters low in order to avoid overfitting. The data features to be matched include official case numbers for each age group and region, deaths, and the share of the B.1.1.7 strain.

[HM 3]
Make reference more specific once Appendix has new structure

The main issue with official case numbers is that they will contain only a fraction of all infections. We thus model official cases as depicted in Figure 1d. We take aggregate estimates of the share of detected cases and use data on the share of PCR tests administered to people with CoViD-19 symptoms. As the share of asymptomatic individuals varies by age group, this gives us age-specific shares (see Figure C.8 for the share of known cases by age group over time in our model). Our estimates suggest that—in the absence of rapid testing—the detection rate is 80% higher on average for individuals above age 80 compared to school age children. Once rapid test become available, confirmation of a positive result is another reason leading to positive PCR tests.

[Klara 2]
Replaced: "whether CoViD-19 symptoms led to a PCR test"

The model is applied to the second and third wave of the CoViD-19 pandemic in Germany, covering the period mid-September 2020 to the end of May 2021. Figure 2 describes the evolution of the pandemic and of its drivers. The black line in Figure 2a shows officially recorded cases; the black line in Figure 2b the Oxford Response Stringency Index (Hale, Atav, Hallas, Kira, Phillips, et al., 2020), which tracks the tightness of non-pharmaceutical interventions. The index is shown for illustration of the NPIs, we never use it directly. For legibility reasons, we transform the index so that lower values represent higher levels of restrictions. A value of zero means all measures incorporated in the index are turned on. The value 1 represents the situation in mid-September, with restrictions on gatherings and public events, masking requirements, but open schools and workplaces. In the seven weeks between mid September and early November, cases increased by a factor of 10. Restrictions were somewhat tightened in mid-October and again in early November. New infections remained constant throughout November before rising again in December, prompting the most stringent lockdown to this date. Schools and daycare centers were closed again, so were customer-facing businesses except for grocery and drug stores. From the peak of the second wave just before Christmas until the trough in mid-February, newly detected cases decreased by almost three quarters. The third wave in the spring of 2021 is associated with the B.1.1.7 strain, which became dominant in March (Figure 2c). In early March, some NPIs were being relaxed; e.g., hairdressers and home improvement stores were allowed to open again



(a) Recorded cases: Empirical and simulated

(b) Stringency of NPIs and infectious contacts

(c) Fraction of B.1.1.7 strain

(d) Tests and vaccinations

Figure 2. Evolution of the pandemic, its drivers, and model fit, September 2020 to May 2021

Note: Data sources are described in Supplementary Material A. Age- and region-specific analogues to Figure 2a can be found in Supplementary Material C.1. For legibility reasons, all lines in Figure 2b are rolling 7-day averages. The Oxford Response Stringency Index is scaled as $2 \cdot (1 - x/100)$, so that a value of 1 refers to the situation at the start of our sample period and 0 means that all NPIs included in the index are turned on. The other lines in Figure 2b show the product of the effect of contact reductions, increased hygiene regulations, and seasonality. See Appendix A.5 for separate plots of the three factors by contact type.

to the public. There were many changes in details of regulations afterwards, but they did not change the stringency index.

By this time, the set of policy instruments had become much more diverse. Around the turn of the year, the first people were vaccinated with a focus on older age groups and medical personnel (Figure 2d). By the end of May, just over 40% had received at least one dose of a vaccine. Around the same time, rapid tests started to replace regular PCR tests for staff in many medical and nursing facilities. These had to be administered by medical doctors or in pharmacies. At-home tests approved by authorities became available in mid-March, rapid test centers were opened, and one test per person and week was made available free of charge. In several states, customers were only allowed to enter certain stores with a recent negative rapid test result. These developments are characteristic of many countries: The initial focus on NPIs to slow the spread of the disease has been accompanied by vaccines and a growing acceptance and use of rapid tests. At broadly similar points in time, novel strains of the virus have started to pose additional challenges.

We draw simulated samples of agents from the population structure in September 2020 and use the model to predict recorded infection rates until the end of May 2021. See Supplementary Material B.9 for a detailed description of this procedure.

The blue line in Figure 2a shows that our model's predictions are very close to officially recorded cases in the aggregate. This is also true for infections by age and geographical region, which are shown in the supplementary materials (Figures C.3 and C.4, respectively).

The effects of various mechanisms can be disentangled due to the distinct temporal variation in the drivers of the pandemic. Next to the stringency index, the three lines in Figure 2b summarize how contact reductions, increased hygiene regulations, and seasonality evolved since early September for each of the three broad contact networks. For example, a value of 0.75 for the work multiplier means that if the environment was the same as in September (levels of infection rates, no rapid tests or vaccinations, only the wildtype virus present), infections at the workplace would be reduced by 25%. The lines show the product of the effect of contact reductions, increased hygiene regulations, and seasonality. Two aspects are particularly interesting. First, all lines broadly follow the stringency index and they would do so even more if we left out seasonality and school vacations (roughly the last two weeks of October, two weeks each around Christmas and Easter, and some days in late May). Second, the most stringent regulations are associated with the period of strong decreases in new infections between late December 2020 and mid-February 2021. The reversal of the trend is associated with the spread of the B.1.1.7 variant. The steep drop in recorded cases during May 2021 is associated with at least weekly rapid tests for 42% of the population, a vaccination rate that rose from 28% to 43%, and seasonality further lowering the relative infectiousness of contacts.

In order to better understand the contributions of rapid tests, vaccinations, and seasonality on the evolution of infections in 2021, Figure 3 considers various scenarios. NPIs are always the same as in the baseline scenario. Figure 3a shows the model fit (the blue line, same as in Figure 2a), a scenario without any of the three factors (red line), and three scenarios turning each factor on individually. Figure 3b does the same for total infections in the model. Figure 3c employs Shapley values (Shapley, 2016) to decompose the difference in total infections between the scenario without any of the three factors and our main specification.

Until mid-March, there is no visible difference between the different scenarios. Seasonality hardly changes, and only few vaccinations and rapid tests were administered. Even thereafter, the effect of the vaccination campaign is surprisingly small at first sight. Whether considering recorded or total infections with only one channel active, the final level is always the highest in case of the vaccination campaign (orange lines). The Shapley value decomposition shows that vaccinations contribute 16% to the cumulative difference between scenarios. Reasons for this are the slow start—it took until March 24th until 10% of the population had received their first vaccination, the 20% mark was reached on April 19th—and the focus on older individuals. These groups contribute less to the spread of the disease than others due to a lower number of contactsas they do not work, do not go to school and tend to live in small households. By the end of our study period, when first-dose vaccination

[Klara 3]
Removed: "mostly"

[Klara 4]
Replaced: "impacting a fall in"

[Klara 5]
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[Klara 6]
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[Klara 7]
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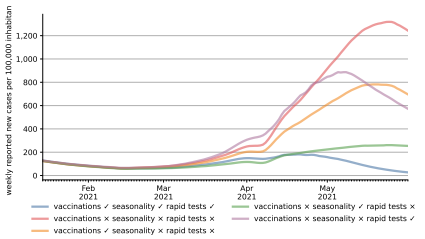
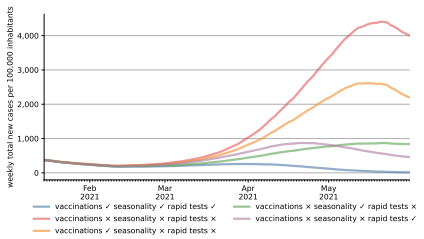
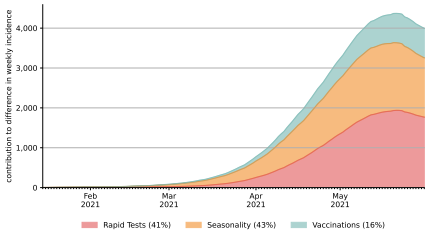


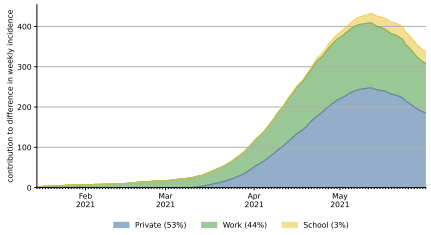
(a) Recorded cases: 2021 scenarios



(b) Total cases: 2021 scenarios



(c) Decomposition of the difference between the scenario without any of the three factors and the main scenario in Figure 3b.



(d) Decomposition of the difference between the scenario without rapid tests and the main scenario in Figure 3b.

Figure 3. The effect of different interventions on recorded and actual infections

Note: The blue line in Figure 3a is the same as in Figure 2a and refers to our baseline scenario, so does the blue line in Figure 3b. The red lines refer to a situation where NPIs evolve as in the baseline scenario and the B.1.1.7 variant is introduced in the same way; vaccinations, rapid tests, and seasonality remain at their January levels. The other scenarios turn these three factors on one-by-one. The decompositions in Figures 3c and 3d are based on Shapley values, which are explained more thoroughly in Appendix B.11

rates reached around 40% of the population, the numbers of new cases would have started to decline. It is important to note that the initial focus of the campaign was to prevent deaths and severe disease. Indeed, the case fatality was rate considerably lower during the third wave when compared to the second (4.4% between October and February and 1.4% between March and the end of May).

[Klara 8]
This needs a source.

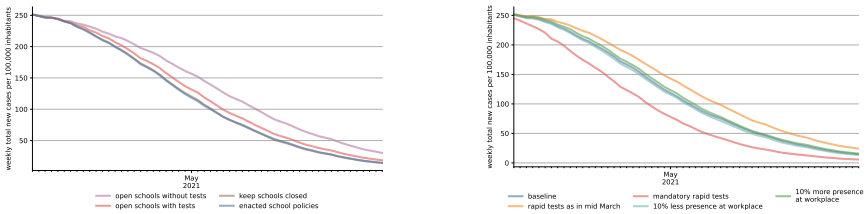
Seasonality has a large effect in slowing the spread of SARS-CoV-2. By May 31, both observed and recorded cases would be reduced by a factor of four if only seasonality mattered. However, in this period, cases would have kept on rising throughout, just at a much lower pace (this is in line with results in Gavenčiak, Monrad, Leech, Sharma, Mindermann, et al., 2021, which our seasonality measure is based on). Nevertheless, we estimate seasonality to be a quantitatively important factor determining the evolution of the pandemic, explaining most of the early changes and 43% of the cumulative difference by the end of May.

A similar-sized effect—41% in the decompositions—comes from rapid testing. Here, it is crucial to differentiate between recorded cases and actual cases. Additional testing means that additional infections will be recorded which would otherwise remain undetected. Figure 3a shows that this effect is large. Until late April, recorded cases are higher in the scenario with rapid testing alone when compared to the setting where none of the three mechanisms are turned on. The effect on total cases, however, is visible immediately in Figure 3b. Despite the fact that only 10% of the population performed weekly rapid tests in March on average, new infections on April 1 would be reduced by 53% relative to the scenario without vaccinations, rapid tests, or seasonality.

So why is rapid testing so effective? In order to shed more light on this question, Figure 3d decomposes the difference in the scenario without rapid tests only (purple line in Figure 3b) and the main specification into the three channels for rapid tests. Tests at schools have the smallest effect, which is largely explained by schools not operating at full capacity during our period of study and the relatively small number of students.[6] Almost 40% come from tests at the workplace. Despite the fact that rapid tests for private reasons are phased in only late, they make up for more than half of the total effect. The reason lies in the fact that a substantial share of these tests is driven by an elevated probability to carry the virus, i.e., showing symptoms of CoViD-19 or following up on a positive test of a household member. The latter is essentially a form of contact tracing, which has been shown to be very effective (Kretzschmar, Rozhnova, Bootsma, Boven, Wijgert, et al., 2020; Contreras et al., 2021; Fetzer and Graeber, forthcoming).

Two of the most contentious NPIs concern schools and mandates to work from home. In many countries, schools switched to remote instruction during the first wave, so did Germany. After the summer break, they were operating at full capac-

6. 18% of our population are in the education sector (pupils, teachers, etc.); 46% are workers outside the education sector.



(a) Effects of different schooling scenarios

(b) Effects of different work scenarios

Figure 4. Effects of different scenarios for policies regarding schools and workplaces.

Note: Blue lines in both figures refer to our baseline scenario; they are the same as in Figure 3b. Interventions start at Easter because there were no capacity constraints for rapid tests afterwards.

ity with increased hygiene measures, before being closed again from mid-December onwards. Some states started opening them gradually in late February, but operation at normal capacity did not resume until the beginning of June. Figure 4a shows the effects of different policies regarding school starting at Easter, at which point rapid tests had become widely available. We estimate the realized scenario to have essentially the same effect as a situation with closed schools. Under fully opened schools with mandatory tests, total infections would have been 6% higher; this number rises to 20% without tests. These effect sizes are broadly in line with empirical studies (e.g., Vlachos, Hertegård, and B. Svaleryd, 2021). To use another metric, the effective weekly reproduction number differs by 0.018 and 0.052, respectively. In light of the large negative effects school closures have on children and parents (Luijten, Muilekom, Teela, Polderman, Terwee, et al., 2021; Melegari, Giallonardo, Sacco, Marcucci, Orecchio, et al., 2021)—and in particular on those with low socioeconomic status—these results in conjunction with hindsight bias suggest that opening schools combined with a testing strategy would have been beneficial. In other situations, and particular when rapid test are not available at scale, trade-offs may well be different.

[HM 4]
Need a back-of the envelope calculation

Figure 4b shows that with a large fraction of workers receiving tests, testing at the workplace has larger effects than mandating employees to work from home. Whether the share of workers working at the usual workplace is reduced or increased by ten percent changes infection rates by 2.5% or less in either direction. Making testing mandatory twice a week—assuming independent compliance by employers and workers of 95% each—would have reduced infections by 23%. Reducing rapid tests offers by employers to the level of March would have increased infections by 13%.

Our analysis has shown that during the transition to high levels of vaccination and possibly thereafter, large-scale rapid testing can substitute for some NPIs. This comes at a fraction of the cost. A week of the fairly strict lockdown in early 2021 is estimated to have cost around 20 Euros per capita (Wollmershäuser, 2021); retail

prices for rapid tests were below one Euro in early June 2021. Despite these large effects, the results on testing likely understate the benefits. Disadvantaged groups are less likely to be reached by testing campaigns relying on voluntary participation (e.g. Stillman and Tonin, 2021); at the same time, these groups have a higher risk to contract CoViD-19 (Robert Koch Institut, 2021). Mandatory tests at school and at the workplace will extend more into these groups. The same goes for individuals who exhibit a low level of compliance with CoViD-19-related regulations. Compared to vaccinations, rapid testing programmes allow a much quicker roll-out, making it arguably the most effective tool to contain the pandemic in the short run.

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Supplementary Material for

The Effectiveness of Strategies to Contain SARS-CoV-2: Testing, Vaccinations, and NPIs

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Tobias Raabe,
Klara Röhrl,
Hans-Martin von Gaudecker

This paper aims to be completely reproducible. The code for the general model can be found at https://github.com/covid-19-impact-lab/sid/ and its documentation at https://sid-dev.readthedocs.io/en/latest/. The code for the application to Germany can be found at https://github.com/covid-19-impact-lab/sid-germany/ with a very rudimentary documentation at https://sid-germany.readthedocs.io/en/latest/.

Appendix A: Data and Parameters

The model is described by a large number of parameters that govern the number of contacts a person has, the likelihood of becoming infected on each contact, the likelihood of developing light or strong symptoms or even dying from the disease as well as the duration each stage of the disease takes.

Most of these parameters can be calibrated from existing datasets or the medical literature or calibrated from surveys and empirical datasets.

A.1 Medical Parameters

This section discusses the medical parameters used in the model, their sources and how we arrived at the distributions used in the model.[7] See Figure 1b for a summary of our disease progression model.

The first medical parameter we need is the length of the period between infection and the start of infectiousness, the so called latent period. We infer it from two other measures that are more common in the medical literature: Firstly, the time between infection and the onset of symptoms, the incubation period. Secondly, the time between the start of infectiousness and the onset of symptoms. We assume that the latency period is the same for symptomatic and asymptomatic individuals.

Once individuals become infectious a share of them goes on to develop symptoms while others remain asymptomatic. We rely on data by Davies, Klepac, Liu, Prem, Jit, et al. (2020) for the age-dependent probability to develop symptoms. It varies from 25% for children and young adults to nearly 70% for the elderly.

The incubation period is usually estimated to be two to twelve days. A meta analysis by McAloon, Collins, Hunt, Barber, Byrne, et al. (2020) comes to the conclusion that "The incubation period distribution may be modeled with a lognormal distribution with pooled μ and σ parameters (95% CIs) of 1.63 (95% CI 1.51 to 1.75) and 0.50 (95% CI 0.46 to 0.55), respectively." For simplicity we discretize this distribution into four bins.

7. Additional information can be found in the online documentation.

The European Centre for Disease Prevention and Control reports that people become infectious between one and two days before symptoms start.[8]

Taking these estimates together, we arrive at a latent period of one to five days.

We assume that the duration of infectiousness is the same for both symptomatic and asymptomatic individuals as evidence suggests little differences in the transmission rates between symptomatic and asymptomatic patients (Yin and Jin (2020)) and that the viral load between symptomatic and asymptomatic individuals are similar (Zou, Ruan, Huang, Liang, Huang, et al. (2020), Byrne, McEvoy, Collins, Hunt, Casey, et al. (2020), Singanayagam, Patel, Charlett, Bernal, Saliba, et al. (2020)). Our distribution of the duration of infectiousness is based on Byrne et al. (2020). For symptomatic cases they arrive at zero to five days before symptom onset (see their figure 2) and three to eight days of infectiousness afterwards.[9] Thus, we arrive at 0 to 13 days as the range for infectiousness among individuals who become symptomatic (see also figure 5).

We use the duration to recovery of mild and moderate cases reported by Bi, Wu, Mei, Ye, Zou, et al. (2020, Figure S3, Panel 2) for the duration of symptoms for non-ICU requiring symptomatic cases. We only disaggregate by age how likely individuals are to require intensive care.[10]

For the time from symptom onset until need for intensive care we rely on data by the US CDC (Stokes, Zambrano, Anderson, Marder, Raz, et al. (2020)) and the OpenABM-Project.

For those who will require intensive care we follow Chen, Qi, Liu, Ling, Qian, et al. (2020) who estimate the time from symptom onset to ICU admission as 8.5 ± 4 days. This aligns well with numbers reported for the time from first symptoms to hospitalization: Gaythorpe, Imai, Cuomo-Dannenburg, Baguelin, Bhatia, et al. (2020) report a mean of 5.76 with a standard deviation of 4. This is also in line with the duration estimates collected by the Robert-Koch-Institut. We assume that the time between symptom onset and ICU takes 4, 6, 8 or 10 days with equal probabilities. As we do not model nursing homes, do not focus on matching deaths and do not use the number of individuals in intensive care to estimate our parameters, these numbers are not important for our empirical results.

We take the survival probabilities and time to death and time until recovery from intensive care from the OpenABM Project. They report time until death to have a mean of 11.74 days and a standard deviation of 8.79 days. To match this approximately we discretize that 41% of individuals who will die from Covid-19 do so after one day in intensive care, 22% day after 12 days, 29% after 20 days and 7%

8. This is similar to He, Lau, Wu, Deng, Wang, et al. (2020) and in line with Peak, Kahn, Grad, Childs, Li, et al. (2020).

9. Viral loads may be detected much later but eight days seems to be the time after which most people are culture negative, as also reported by Singanayagam et al. (2020).

10. The length of symptoms is not very important in our model given that individuals mostly stop being infectious before their symptoms cease.

after 32 days. Again, we rescale this for every age group among those that will not survive. For survivors the OpenABM Project reports a mean duration of 18.8 days until recovery and a standard deviation of 12.21 days. We discretize this such that of those who recover in intensive care, 22% do so after one day, 30% after 15 days, 28% after 25 days and 18% after 45 days.

A.2 The Synthetic Population

[Klara 9]
To be written

We build a synthetic population based on the German microcensus (Forschungsdatenzentren Der Statistischen Ämter Des Bundes Und Der Länder, 2018). We only use private households, i.e. exclude living arrangements such as nursing homes as non-private households vary widely in size and it is very difficult to know which contacts take place in such households.

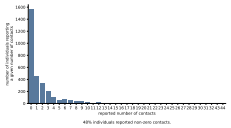
We sample households to build our synthetic population of over one million households keeping for each individual their age, gender, occupation and whether they work on Saturdays and Sundays.

A.3 Number of Contacts

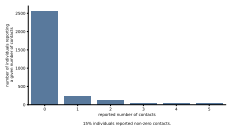
We calibrate the parameters for the predicted numbers of contacts from contact diaries of over 2000 individuals from Germany, Belgium, the Netherlands and Luxembourg (Mossong, Hens, Jit, Beutels, Auranen, et al., 2008). Each contact diary contains all contacts an individual had throughout one day, including information on the other person (such as age and gender) and information on the contact. Importantly, for each contact individuals entered of which type the contact (school, leisure, work etc.) was and how frequent the contact with the other person is.

Simplifying the number of contacts, we arrive at the following distributions of the numbers of contacts by contact type.

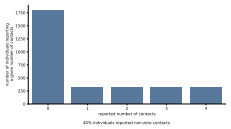
An exception where we do not rely on the data by Mossong et al. (2008) are the household contacts. Since household are included in the the German microcensus (Forschungsdatenzentren Der Statistischen Ämter Des Bundes Und Der Länder, 2018) on which we build our synthetic population we simply assume for the household contact model that individuals meet all other household members every day.



(a) Number of Non Recurrent Other Contacts



(b) Number of Daily Recurrent Other Contacts



(c) Number of Weekly Recurrent Other Contacts

Figure A.1. Number of Contacts of the Other Contact Type

Note: Other contacts include all contacts that are not household members, school contacts or work contacts, for example leisure contacts or contacts during grocery shopping. The planned number of contacts is reduced by policies, seasonality and individual responses to events such as receiving a positive rapid test to the number of actual contacts with transmission potential. In the model it is sampled every day which of the numbers of non recurrent contacts a person is planned to have. Note that the contact diaries include such high values that super spreading events are well possible in our model through non recurrent other models. We assume that individuals in households with children or teachers or retired individuals have additional non recurrent contacts during school vacations to cover things like family visits or travel during vacations. We estimate this to be on average 0.5 additional contacts per vacation day. For the recurrent other contacts, individuals are assigned to groups that are time constant and that meet daily or weekly. The share of individuals who attend in a way that has transmission potential is reduced by policies, seasonality and individual responses to events such as receiving a positive rapid test. For weekly contacts, individuals are assigned to up to four groups that are time constant and that meet weekly. The day on which meetings take place varies between groups but stays the same for each group.

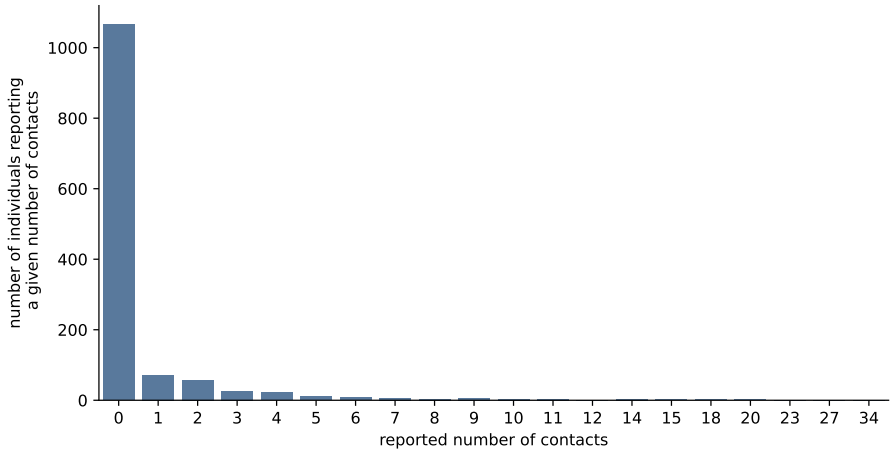


Figure A.2. Number of Non Recurrent Work Contacts

Note: In the model it is sampled every day which of these numbers of contacts a working person is planned to have. Note that the contact diaries include such high values that super spreading events are well possible in our model. The planned number of contacts is reduced by policies, seasonality and individual responses to events such as receiving a positive rapid test to the number of actual contacts with transmission potential. Work contacts only take place between working individuals.

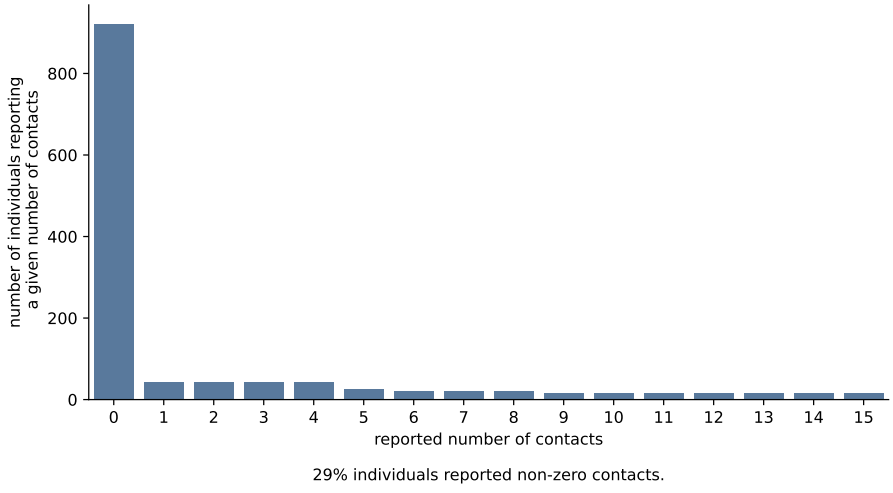


Figure A.3. Number of Daily Recurrent Work Contacts

Note: Working individuals are assigned to groups that are time constant and that meet daily to match the given distribution of daily work contacts. You can think of these as for example colleagues with which one shares an office space. The share of individuals who attend in a way that has transmission potential is reduced by policies (such as a work from home mandate), seasonality and individual responses to events such as receiving a positive rapid test. Work contacts only take place between working individuals.

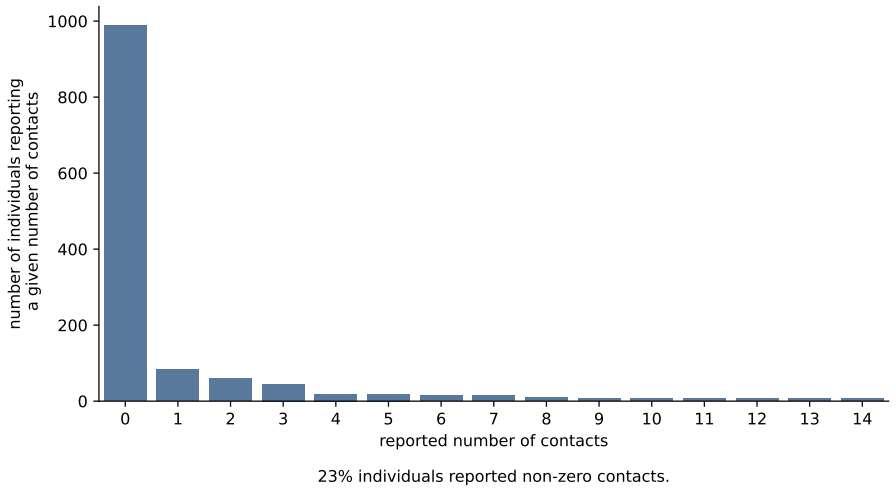


Figure A.4. Number of Weekly Recurrent Work Contacts

Note: Working individuals are assigned to up to 14 groups that are time constant and meet weekly. Groups are scheduled to meet on separate days of the work week. These contact models cover weekly team meetings etc. The share of individuals that attend in a way that has transmission potential is reduced by policies, seasonality and individual responses to events such as receiving a positive rapid test. Work contacts only take place between working individuals.

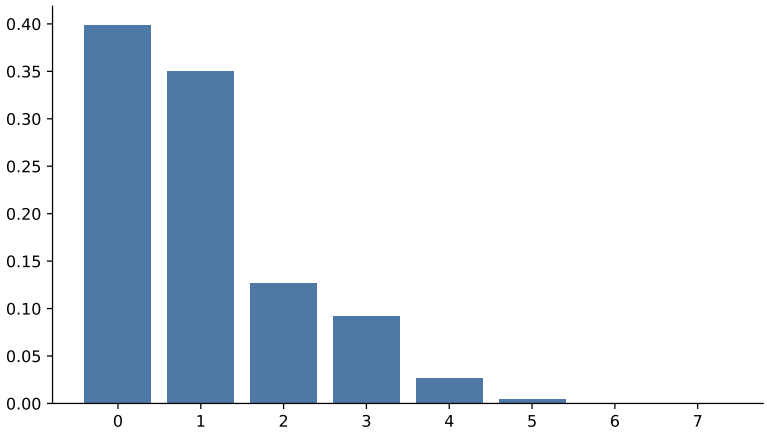


Figure A.5. Number of Household Contacts

Note: Every individual meets all other household members every day. The German microcensus sampled full households such that our synthetic population automatically fits population characteristics such as size and age distribution.

A.4 Contacts by age

As mentioned in section B.5, the probability that two individuals are matched can depend on background characteristics. In particular, we allow this probability to depend on age and county of residence. While we do not have good data on geographical assortativity and just roughly calibrate it such that 80% of contacts are within the same county, we can calibrate the assortative mixing by age from the same data we use to calibrate the number of contacts.

[HM 5]
Redo A.6 / A.7 with total number of contacts or better add a similar figure showing total number of contacts by age in all networks

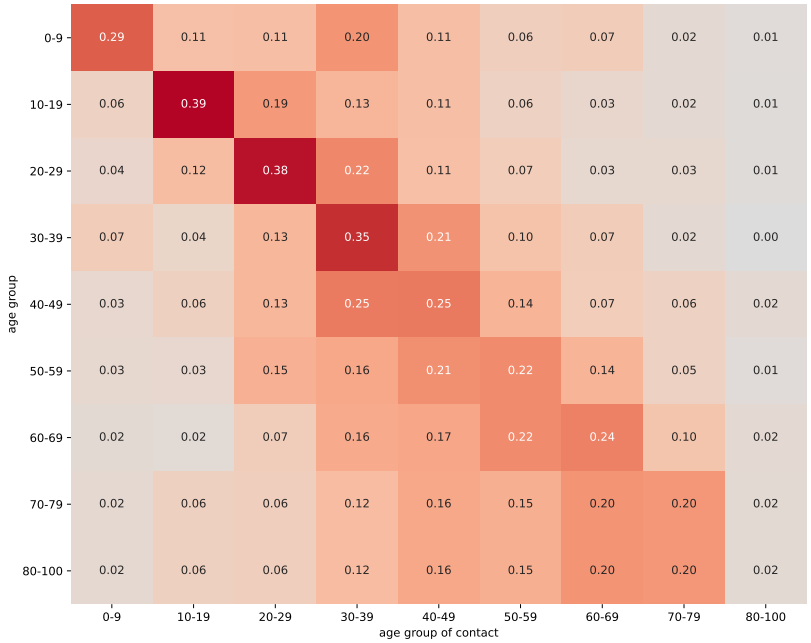


Figure A.6. Distribution of Non Recurrent Other Contacts by Age Group

Note: The figure shows the distribution of non recurrent other contacts by age group. A row shows the share of contacts a certain age group has with all other age groups. Higher values are colored in darker red tones. The diagonal represents the share of contacts with individuals from the same age group.

Figure A.6 shows that assortativity by age is especially strong for children and younger adults. For older people, the pattern becomes more dispersed around their own age group, but within-age-group contacts are still the most common contacts.

Figure A.7 shows that assortativity by age is also important among work contacts.

Our two other types of contacts, households and schools, get their assortativity by construction. Schools are groups where the same children of the mostly same age and county meet with teachers every day. Household composition follows directly from the German microcensus data we use to construct our synthetic population.

A.5 Policies and Seasonality

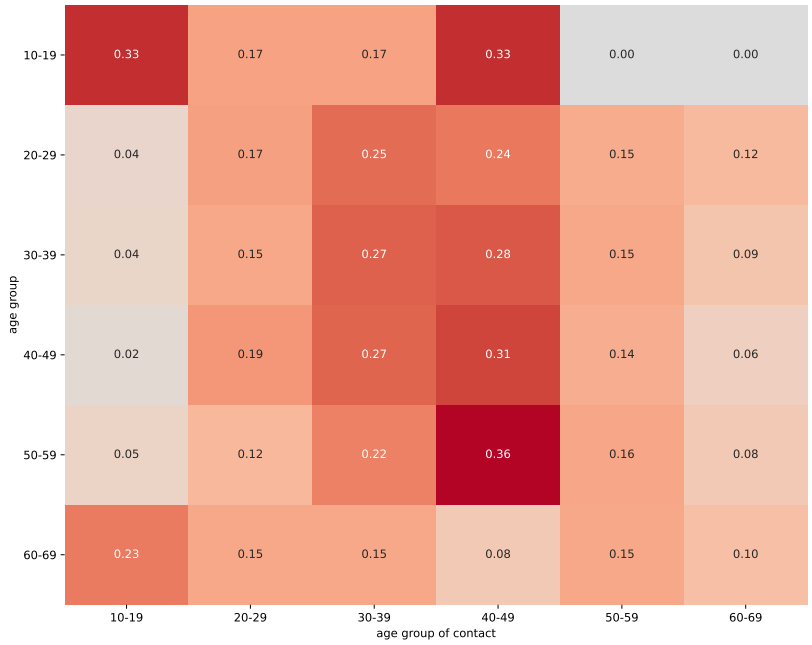


Figure A.7. Distribution of Random Work Contacts by Age Group

Note: The figure shows the distribution of non recurrent work contacts by age group. A row shows the share of contacts a certain age group has with all other age groups. Higher values are colored in darker red tones. The diagonal represents the share of contacts with individuals from the same age group. We only show age groups that have a significant fraction of working individuals.

In our empirical application we distinguish four groups of contact types: households, education, work and other contacts. For households we assume that the individuals' contacts in their households do not change over our estimation period. For nurseries, preschools and schools we implement vacations as announced by the German federal states as well as school closures, emergency care and A / B schooling where only one half of students attends every other week or day. For the moment we ignore that lack of childcare leads working parents to stay home. An approximation of the share of contacts still taking place with the different school regulations can be found in Figure A.8.

For our work models[11] we use the reductions in work mobility reported in the Google Mobility Data (Google, 2021) to calibrate our work policies. Reductions in work contacts are not random but governed through a work contact priority where the policy changes the threshold below which workers stay home. Figure A.9 shows the share of workers that go to work in our model over time.

For both work and school contacts we assume that starting November with the lockdown light in Germany, hygiene measures (such as masks, ventilation and hand

11. We distinguish non-recurrent work contacts, daily work contacts and weekly work contacts.

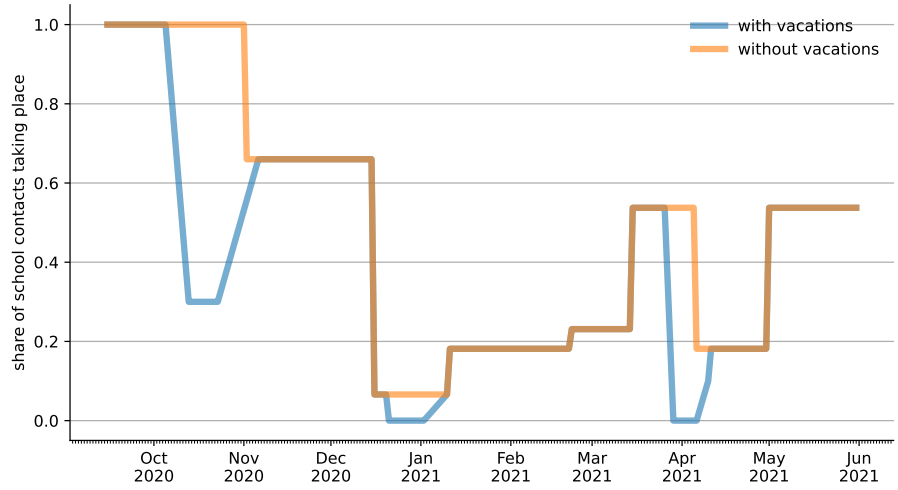


Figure A.8. School Multiplier With and Without Vacations Factored In

Note: The dates on which schools have vacation are decided at the federal level. Vacations are directly implemented in our model with no school contacts taking place on weekends and during vacations (by federal state) just like the schooling mode (full operation, emergency care, rotating schemes with half class sizes etc.). The figure is thus only an illustration that roughly shows the share of contacts taking place compared to pre-pandemic level with and without vacations. The difference between the lines show when vacations take place and to what degree. For example all states have fall vacations but the timing varies strongly between states.

washing) became more strict and more conscientiously observed, leading to a reduction of 33% in the number of contacts with the potential to transmit Covid-19.

For the last group of contacts, which cover things like leisure activities, grocery shopping, etc., we have no reliable data by how much policies reduce them. In addition, they are likely to be affected by social and psychological factors such as pandemic fatigue and vacations. Because of this we estimate them like the infection probabilities to fit the time series data. We use very few change points and tie them to particular events such as policy announcements or particular holidays. Because of the scarce data situation we cannot distinguish between a hygiene factor (such as mask wearing) during meetings and physical distancing (such as virtual meetings with friends).

[Klara 10]
@Janos: Maybe make more concrete when the estimation is finished which phases we have and why the switching points are where they are.

Another potentially important factor for a contact to lead to an infection is the seasonality (Carlson, Gomez, Bansal, and Ryan, 2020; Kühn, Abele, Mitra, Koslow, Abedi, et al., 2020) There are two channels through which seasonality affects the infectiousness of contacts. One has to do with the physical conditions like the temperature and the humidity. The other has to do with where people meet. Especially leisure contacts are more likely to take place outdoors and individuals are more likely to have windows open when the weather is nicer. To capture both channels we allow for other contacts to have a higher seasonality than our other contact models. Figure A.11 shows our seasonality factors.

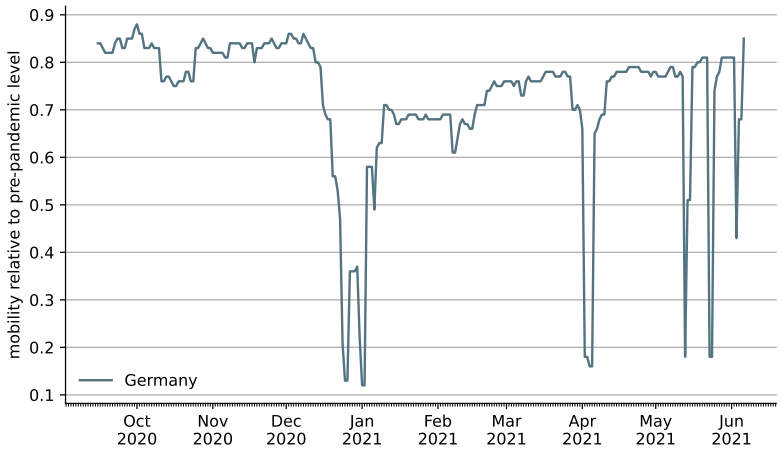


Figure A.9. Share of Workers with Work Contacts

Note: The figure shows the work mobility as reported by Google (2021). We take this as a proxy of the share of workers who are not in home office, i.e. who still have physical work contacts. The figure interpolates over weekends as we handle weekend effects through information on work on weekends in the German census data we use. The figure shows the share aggregated over Germany as a whole. To capture the effect that local policies, school vacations and public policies have on work contacts we use the data on the level of the federal states to determine which workers go to work depending on the state they live in.

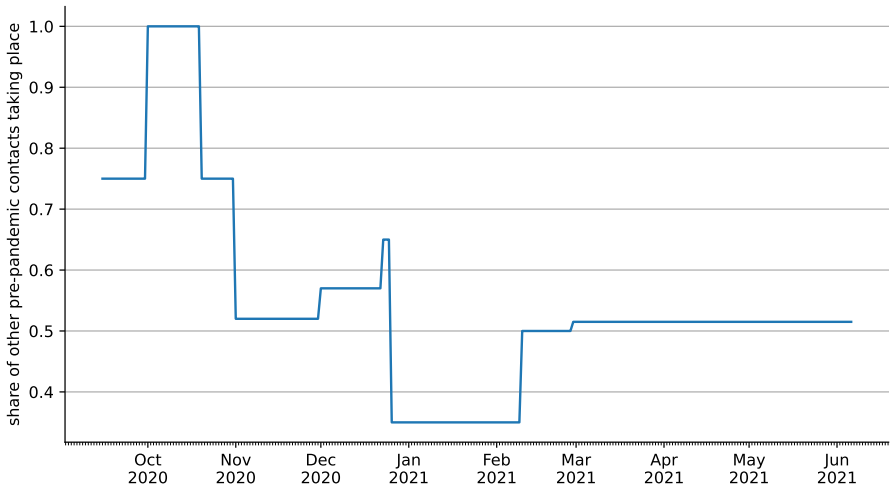


Figure A.10. Share of Pre-Pandemic Other Contacts Taking Place with Infection Potential

Note: All values are estimated. We try to use as little switching points as possible and tie them to political events (such as lockdown announcements) unless changes are used to capture anticipation or pandemic fatigue (for example we model an anticipation of the November lockdown and model lockdown fatigue in early March).

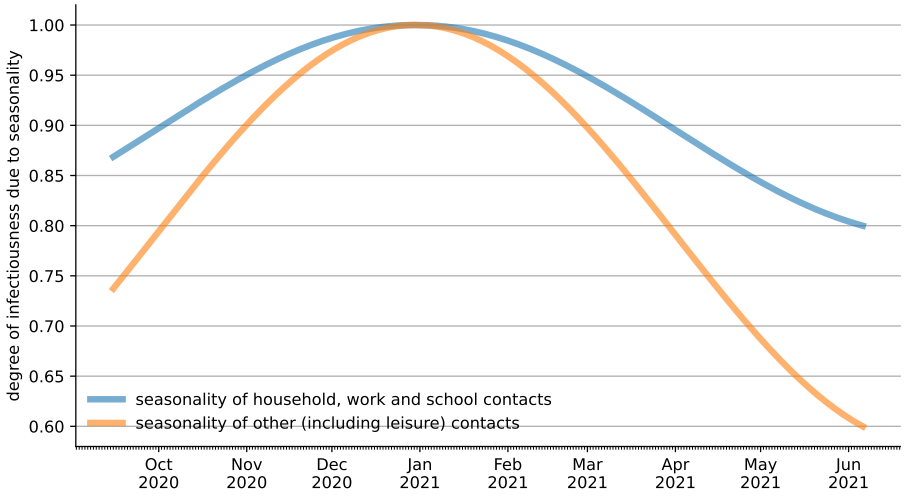


Figure A.11. Seasonality by Type of Contact

Note: We model seasonality as a factor that reduces the probability of infection of all encounters. The factor depends on the day and is calculated from a sinus shaped function with its maximum on January 1st. Since seasonality can affect the transmission both through physical conditions such as temperature and humidity as well as through the numbers of contacts that take place outside we assume two seasonality factors. One for other contacts which we expect to be strongly affected by fairer weather with a maximum reduction of 42% in the infection probability. The other seasonality only makes contacts up to 21% less infectious and is applied to household, work and school contacts.

A.6 Rapid Test Demand

In our model, there are five reasons why rapid tests are done:

(1) someone plans to have work contacts

(2) someone is an employee of an educational facility or a school pupil

(3) a household member has tested positive or developed symptoms

(4) someone has developed symptoms but has not received a PCR test

(5) someone plans to participate in a weekly non-work meeting

[Janos 2]
Add a section on how we calibrate rapid test demand; Mainly describe the datapoints we have and say that we usually interpolate linearly in between data points. (Only exception to that is private rapid test demand, which we fit to data)

For work contacts, we know from the COSMO study (Betsch, Korn, Felgendreff, Eitze, Schmid, et al. (2021), 20th/21st of April) that 60% of workers who receive a test offer by their employer regularly use it. We assume this share to be time constant.

In addition, there are some surveys that allow us to trace the expansion of employers who offer tests to their employees. Mid march, 20% of employers offered tests to their employees (DIHK, 2021). In the second half of March, 23% of employees reported being offered weekly rapid tests by their employer (Ahlers, Lübker, and Jung, 2021). This share increased to 60% until the first days of April Fernsehen (2021).

[Klara 11]
ToDo: Find the survey that the ZDF is citing here

Until mid April 70% of workers were expected to receive a weekly test offer (ÄrzteZeitung, 2021). However, according to surveys conducted in mid April (Betsch et al., 2021), less than two thirds of individuals with work contacts receive a test offer. Starting on April 19th employers were required by law to provide two weekly tests to their employees (Bundesanzeiger, 2021). We assume that compliance is incomplete and only 80% of employers actually offer tests.

We assume that employees in educational facilities start getting tested in 2021 and that by March 1st 30% of them are tested weekly. The share increases to 90% for the week before Easter. At that time both Bavaria (Bayrischer Rundfunk, 2021) and Baden-Württemberg (Ministerium für Kultus, Jugend und Sport Baden Württemberg, 2021) were offering tests to teachers and North-Rhine Westphalia[12] Deutsche Presse Agentur (2021) and Lower Saxony (Sueddeutsche Zeitung, 2021b) were already testing students and tests for students and teachers were already mandatory in Saxony (Sueddeutsche Zeitung, 2021a). After Easter we assume that 95% of teachers get tested twice per week.

Tests for students started later[13] (Ministerium für Kultus, Jugend und Sport Baden Württemberg, 2021) so we assume that they only start in February and only 10% of students get tested by March 1st. Relying on the same sources as above we approximate that by the week before Easter this share had increased to 40%.[14]

12. https://www.land.nrw/de/pressemitteilung/umfassende-informationen-fuer-die-schulen-zu-corona-selbsttests-fuer-schuelerinnen
13. https://www.land.nrw/de/pressemitteilung/umfassende-informationen-fuer-die-schulen-zu-corona-selbsttests-fuer-schuelerinnen
14. https://www.land.nrw/de/pressemitteilung/umfassende-informationen-fuer-die-schulen-zu-corona-selbsttests-fuer-schuelerinnen,

After Easter the share of students receiving twice weekly tests is set to 75%. This as based on tests becoming mandatory becoming mandatory in Bavaria after Easter break[15] and on the 19th in Baden-Württemberg[18].

To limit our degrees of freedom, we only have one parameter that governs how many individuals do a rapid test because of any of the private demand reasons (own symptoms but no PCR test, planned weekly leisure meeting or a symptomatic or positively tested household member).

We assume that there is no private rapid test demand until March when both the citizens' tests and rapid tests for lay people started to become available [19] and other access to rapid tests was very limited.

According to the COSMO study[20] 63% would have been willing to take a test in the round of 23rd of February 2021 when an acquaintance would have tested positive. Since this is only asking for willingness not actual behavior and the demand when meeting with friends is very likely lower, we take this as the upper bound of private rapid test demand which is reached on May 4th. To cover that many people are likely to have sought and done their first rapid test before the Easter holidays to meet friends or family, we let the share of individuals doing rapid tests in that time increase more rapidly than before and after. By end of March 25% of individuals would do a rapid test due to a private reason.

All shares of individuals who would take a rapid test if the conditions were met can be seen in Figure A.12.

[Janos 3]
Talk about the interpretation of each line.

15. Bavaria[16], in North-Rhine Westphalia on April 12th[17], https://bit.ly/2QHilX3
18. https://bit.ly/3vuetaD, https://bit.ly/3vuetaD
19. https://bit.ly/3ehmGcj, https://bit.ly/3xJCIn8
20. https://bit.ly/2QSFAgR

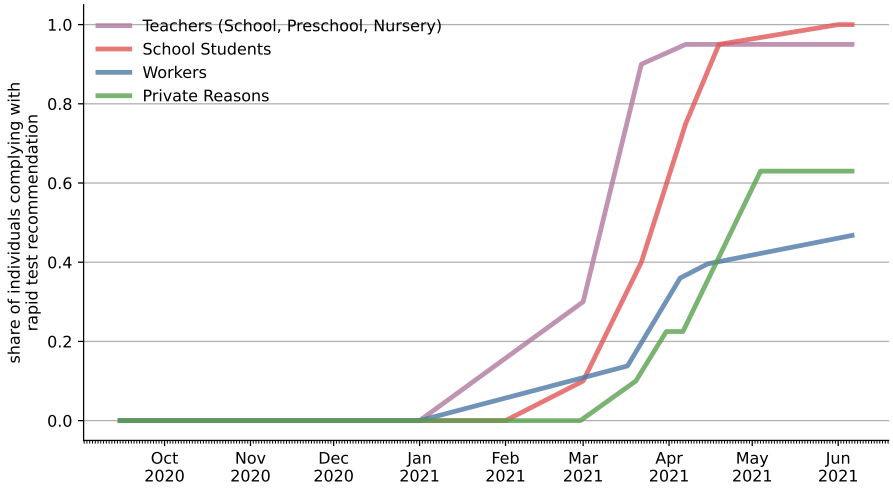


Figure A.12. Share of Individuals Doing a Rapid Test.

Note: Rapid test demand can be triggered by individuals planning to have education contacts, work contacts, developing symptoms without access to a PCR test, having a household member with a positive test or symptoms. In each case whether a rapid test is done depends on how long it has been since the individual's last rapid test and her individual compliance parameters. As an example, take a worker in May. In that time workers are encouraged to test themselves twice weekly but there is no general requirement to test themselves. If the worker has not done a test within the last four days in our model she will demand a test if her (time-constant) compliance parameter belongs to the upper 60% in the population.

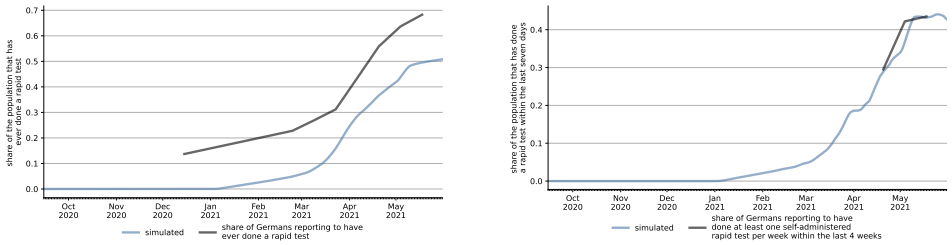


Figure A.13. Share of Individuals With Rapid Tests

Note: The figure compares the share of individuals who have ever done a rapid test or done a rapid test within the last week in our simulations to the shares reported in the COVID-19 Snapshot Monitoring Survey. The left panel compares the share of individuals who have ever done a rapid test. The right panel compares the share of individuals who have done a rapid test within the last seven days in our simulation compared to the share reporting to have done at least weekly rapid tests in the last four weeks in the COSMO survey. Overall our calibration of rapid tests are slightly conservative. The overall share is below that in the study. We fit the share of weekly tests quite exactly. However, the study only covers adults while our share also includes children who are tested very regularly when attending school.

Appendix B: Detailed Model Description

[Klara 12]
Philipp: we should have a truly formal description of our model

B.1 Literature Review

We build on two strands of literature: Recent extensions of the epidemiological SEIR model and agent-based simulation models.

The traditional SEIR model is not fine-grained enough to model nuanced policies. This has motivated a large number of researchers to extend the standard model to allow for more heterogeneity and flexibility. Examples are Grimm, Mengel, and Schmidt (2020), Donsimoni, Glawion, Plachter, and Wälde (2020) and Acemoglu, Chernozhukov, Werning, and Whinston (2020) who develop multi group SEIR models to analyze the effects of targeted lockdowns and Berger, Herkenhoff, and Mongey (2020) who extend the SEIR model to analyze testing and conditional quarantines. For a more comprehensive review see Avery, Bossert, Clark, Ellison, and Ellison (2020). Others have used the results of a standard SEIR model as input for economic models that estimate the cost of policies (e.g. Dorn, Khailaie, Stöckli, Binder, Lange, et al. (2020)).

While the popularity of the SEIR model is mainly due to its simplicity, the extensions are quite complex. It is unlikely that there will be a SEIR model that combines all proposed extensions. Moreover, the extensions do not address other key issues: The main parameter of the SEIR model, the basic reproduction number (R_0), is not policy-invariant. It is a composite of the number of contacts each person has and the infection probability of the contacts. In fact, policy simulations are done by setting R_0 to a different value but it is hard to translate a real policy into the value of R_0 it will induce. In other words, SEIR models are not suited for evaluating the effect of policies which have never been experienced before.

Another commonly used model class in epidemiology are agent-based simulation models. In these models individuals are simulated as moving particles. Infections take place when two particles come closer than a certain contact radius (e.g. Silva, Batista, Lima, Alves, Guimarães, et al. (2020) and Cuevas (2020)). While the simulation approach makes it easy to incorporate heterogeneity in disease progression, it is hard to incorporate heterogeneity in meeting patterns. Moreover, policies are modeled as changes in the contact radius or momentum equation of the particles. The translation from real policies to corresponding model parameters is a hard task.

Hinch, Probert, Nurtay, Kendall, Wymatt, et al. (2020) is a recent extension of the prototypical agent-based simulation model that replaces moving particles by contact networks for households, work and random contacts. This model is similar in spirit to ours but focuses on contact tracing rather than social distancing policies.

The above assessment of epidemiological models is not meant as a critique. We are aware that these models were not designed to predict the effect of fine-grained social distancing policies in real time and are very well suited to their purpose. We invite epidemiologists to provide feedback and collaborate to improve our model.

B.2 Summary

To predict and quantify the effects of a wide variety of fine-grained social distancing policies, vaccinations and rapid testing, we propose a different model structure. Our model inherits many features from prototypical agent-based simulation models but replaces the contacts between moving particles by contacts between individuals who work, go to school, live in a household and enjoy leisure activities.

The structure of the model is depicted in Figure 1a.

We distinguish between eight types of contact models which are all listed in Figure 1a: households, recurrent and random work contacts, recurrent and random leisure contacts, and nursery, preschool, and school contacts.

The number of contacts is translated into infections by a matching algorithm. There are different matching algorithms for recurrent contacts (e.g. classmates, family members) and non-recurrent contacts (e.g. clients, contacts in supermarkets). All types of contacts can be assortative with respect to geographic and demographic characteristics.

The infection probabilities of contacts vary with contact type, age of the susceptible person, and the virus strain of the infected person. Moreover, they follow a seasonal pattern. The strength of the seasonality effect is higher for contacts that are easy to be moved to an outside location in summer (such as leisure contacts) and smaller for contacts that take place inside even in summer (e.g. work contacts).

Once a person is infected, the disease progresses in a fairly standard way which is depicted in Figure 1b. Asymptomatic cases and cases with mild symptoms are infectious for some time and recover eventually. Cases with severe symptoms additionally require hospitalization and lead to either recovery or death.

After rapid tests become available, people who work or go to school can receive rapid tests there. Moreover, people can decide to make a rapid test if they develop symptoms, have many planned contacts or observe cases in their contact network. People who have a positive rapid test demand a confirmatory PCR test with a certain probability. Moreover, PCR tests can be demanded because of symptoms or randomly.

[Klara 13]
at the moment it's implemented as planing to participate in a weekly leisure meeting. Should we be more explicit here?

This rich model of PCR and rapid tests leads to a share of detected cases that varies over time and across age groups. It also allows to quantify the effect of changes in testing policies on the dynamic of infections.

People who have symptoms, received a positive test, or had a risk contact can reduce their number of contacts across all contact types endogenously. The extent to which this is done is calibrated from survey data.

The model makes it very simple to translate policies into model quantities. For example, school closures imply the complete suspension of school contacts. A strict lockdown implies shutting down work contacts of all people who are not employed in a systemically relevant sector. It is also possible to have more sophisticated policies

that condition the number of contacts on observable characteristics, risk contacts or health states.

An important feature of the model is that the number of contacts an individual has of each contact type can be calibrated from publicly available data (Mossong et al., 2008). This in turn allows us to estimate policy-invariant infection probabilities from time series of infection and death rates using the method of simulated moments (McFadden, 1989). Since the infection probabilities are time-invariant, data collected since the beginning of the pandemic can be used for estimation. Moreover, since we model the testing strategies that were in place at each point in time, we can correct the estimates for the fact that not all infections are observed.

The model has a very modular structure and can easily be extended to distinguish more contact types, add more stages to the disease progression, implement new policies or test demand models. The main bottleneck is not complexity or computational cost but the availability of data to calibrate the additional model features.

B.3 Modeling Numbers of Contacts

Consider a hypothetical population of 1,000 individuals in which 50 were infected with a novel infectious disease. From this alone, it is impossible to say whether only those 50 people had contact with an infectious person and the disease has an infection probability of 1 per contact or whether everyone met an infectious person but the disease has an infection probability of only 5 percent per contact. SEIR models do not distinguish contact frequency from the infectiousness of each contact and combine the two in one parameter that is not invariant to social distancing policies.

To model social distancing policies, we need to disentangle the effects of the number of contacts of each individual and the effect of policy-invariant infection probabilities specific to each contact type. Since not all contacts are equally infectious, we distinguish different contact types.

The number and type of contacts in our model can be easily extended. Each type of contacts is described by a function that maps individual characteristics, health states and the date into a number of planned contacts for each individual. This allows to model a wide range of contact types.

In our empirical application we distinguish the following contact types that are depicted in Figure 1a and can be further grouped in the categories household, work, education and others.

types of contacts:

- Households: Each household member meets all other household members every day.
- Recurrent work contacts, capturing contacts with coworkers, repeating clients and superiors. Some of these recurrent contacts take place on every workday, others just once per week.

[HM 6]

I started updating this to understand it better myself. In the end, I think it will be useful to group into HH / work / schools and add an introductory sentence for each group. E.g., that work is for everybody who is working — except there is a different model for teachers (?), ...

- Random work contacts: Working adults have contacts with randomly drawn other people, which are assortative in geographical location and age.
- Schools: Each student meets all of his classmates every day. Class sizes are calibrated to be representative for Germany and students have the same age. Schools are closed on weekends and during vacations, which vary by states. School classes also meet six teachers everyday and some of the teachers meet each other.
- Preschools: Children who are at least three years old and younger than six may attend preschool. Each group of nine children interacts with the same two adults every day. The children in each group are of the same age. The remaining mechanics are similar to schools.
- Nurseries: Children younger than three years may attend a nursery and interact with one adult. The age of the children varies within groups. The remaining mechanics are similar to schools.
- Random other contacts: Contacts with randomly drawn other people, which are assortative with respect to geographic location and and age group. This contact type reflects contacts during leisure activities, grocery shopping, medical appointments, etc..
- Recurrent other contacts representing contacts with friends neighbors or family members who do not live in the same household. Some of these contacts happen daily, others only once per week.

The number of random and recurrent contacts at the workplace, during leisure activities and at home is calibrated with data provided by Mossong et al. (2008). For details see Section B.3. In particular, we sample the number of contacts or group sizes from empirical distributions that sometimes depend on age. It would also be possible to use economic or other behavioral models to predict the number of contacts.

B.4 Reducing Numbers of Contacts via NPIs

Our model makes it very easy to model a wide range of NPIs, either in isolation or simultaneously. This is important for two reasons: Firstly, it allows to predict and quantify the effect of novel NPIs. Secondly, it allows to model the actually implemented policy environment in great detail, which is necessary to use use the full time series of infections and fatality rates to estimate the model parameters.[21]

Instead of thinking of policies as completely replacing how many contacts people have, it is often more helpful to think of them as adjusting the pre-pandemic

21. See Avery et al. (2020) for an explanation why it can be harmful to use too long time series to estimate simple SEIR type models.

number of contacts. Therefore, we implement policies as a step that happens after the number of contacts is calculated but before individuals are matched.

On an abstract level, a policy is a functions that modifies the number of contacts of one contact type. This function can be random or deterministic. For example, school closures simply set all school contacts to zero. A work from home mandate leads to a share of workers staying home every day whereas those who cannot work from home are unaffected. Hygiene measures at work randomly reduce the number of infectious contacts for all workers who still go to work.

Policies can also interact. For example, school vacations are temporally reducing school contacts to zero while at the same time increasing other contacts to account for increased leisure activities and family visits during this time. This is important to reproduce the finding that school vacations do not reduce infection numbers even though schools lead to infections when open (Isphording, Lipfert, and Pestel, 2021).

The most complex policies are typically found in the education sector. Since the beginning of 2021 schools have switched back and fourth between full closures, split class approaches with alternating schedules for some or all age groups and reopening while maintaining hygiene measures. On top of that there are different policies for allowing young students whose parents work full time to attend school even on days where they normally would not. For details on how we calibrate these policies see Section A.5.

Importantly, policies can depend on the health states of participating individuals. This allows to quarantine entire school classes if one student tested positive or to implement official or private contact tracing.

For some policies the exact effect on each contact type is not easy to determine. If this refers to a policy has been active during the estimation period, it is possible to estimate such parameters by fitting the model to time series data of infection rates. This is only possible if the policy was not active during the whole estimation period and thus the infection probabilities can be identified separately. We do this to account for hygiene measures at school and in the workplace that have been in effect since November 2020.

Not all things that reduce contacts compared to the pre-pandemic level are driven by NPIs. Therefore, we also model endogenous contact reductions that can depend on the health state of individuals, known risk contacts or the local incidence of infections. Examples are strong contact reductions for symptomatic individuals or those who have a positive PCR or rapid tests or contact reductions when a houshold member tested positive. The extent to which contacts are reduced can be calibrated from surveys. For an application of our model showcasing private contact tracing in the context of the Christmas holidays see Gabler, Raabe, Röhrl, and Gaudecker (2020).

B.5 Matching Individuals

The empirical data described above only allows to estimate the number of contacts each person has. In order to simulate transmissions of Covid-19, the numbers of contacts has to be translated into actual meetings between people. This is achieved by a matching algorithm:

As described in section B.3, some contact types are recurrent (i.e. the same people meet regularly), others are non-recurrent (i.e. it would only be by accident that two people meet twice). The matching process is different for recurrent and non recurrent contact models.

Recurrent contacts are described by two components: 1) A set of time invariant groups, such as school classes. The groups can be sampled from empirical data or created by randomly matching simulated individuals into groups. 2) A deterministic or random function that takes the value 0 (non-participating) and 1 (participating) and can depend on the weekday, date and health state. This can be used to model vacations, weekends or symptomatic people who stay home (see section B.4 for details).

The matching process for recurrent contacts is then extremely simple: On each simulated day, every person who does not stay home meets all other group members who do not stay home. The assumption that all group members have contacts with all other group members is not fully realistic, but a good approximation to reality, especially in light of the suspected role of aerosol transmission for Covid-19 (Anderson, Turnham, Griffin, and Clarke, 2020; Morawska, Tang, Bahnfleth, Bluyssen, Boerstra, et al., 2020). Alternatively, the infection probability of recurrent contact types can be interpreted as being the product of a true infection probability and the probability that an actual contact takes place.

The matching in non-recurrent contact models is more difficult and implemented in a two stage sampling procedure to allow for assortative matching. Currently most contact models are assortative with respect to age (it is more likely to meet people from the same age group) and county (it is more likely to meet people from the same county) but in principle any set of discrete variables can be used. This set of variables that influence matching probabilities introduce a discrete partition of the population into groups. The first stage of the two stage sampling process samples on the group level. The second stage on the individual level.

The algorithm works as follows: First we randomly draw a contact type and individual. For each contact of the drawn contact type that person has, we first draw the group of the other person (first stage). Next, we calculate the probability to be drawn for each member of the group, based on the number of remaining contacts, i.e. people who have more remaining contacts are drawn with a higher probability. The probabilities have to be re-calculated each time because with each matched contact, the number of remaining contacts changes. We then draw the other individual, determine whether an infection takes place and if so update the health state of the

newly infected person. Finally, we reduce the number of remaining contacts of the two matched individuals by one.

[Janos 4]
Add formulae here.

The recalculation of matching probabilities in the second stage is computationally intensive because it requires summing up all remaining contacts in that group. Using a two stage sampling process where the first stage probabilities remain constant over time makes the matching computationally much more tractable because the number of computations only increases quadratically in the size of the second group and not quadratically in the size of the entire simulated population.

B.6 Course of the Disease

The disease progression in the model is fairly standard. It is depicted in Figure 1b and the values and source of the relevant parameters are describes in Section A.1.

First, infected individuals will become infectious after one to five days. Overall, about one third of people remain asymptomatic. The rest develop symptoms about one to two days after they become infectious. Modeling asymptomatic and pre-symptomatic cases is important because those people do not reduce their contacts nor do they have an elevated probability to demand a test. Thus they can potentially infect many other people (Donsimoni et al., 2020). The probability to develop symptoms with Covid-19 is highly age dependent with 75% of children not developing clinical symptoms (Davies et al., 2020).

A small share of symptomatic people will develop strong symptoms that require intensive care. The exact share and time span is age-dependent. An age-dependent share of intensive care unit (ICU) patients will die after spending up to 32 days in intensive care. Moreover, if the ICU capacity was reached, all patients who require intensive care but do not receive it die.

It would be easy to make the course of disease even more fine-grained. For example, we could model people who require hospitalization but not intensive care. So far we opted against that because only the intensive care capacities are feared to become a bottleneck in Germany.

We allow the progression of the disease to be stochastic in two ways: Firstly, state changes only occur with a certain probability (e.g. only a fraction of infected individuals develops symptoms). Secondly, the number of periods for which an individual remains in a state is drawn randomly. The parameters that govern these processes are taken from the literature [22].

[Janos 5]
Replace this by a link to the relevant table with parameters in the data appendix, once we have that table.

B.7 Testing

Having a realistic model of PCR and rapid tests is crucial for two reasons: Firstly, only via a testing model the simulated infections from the model can be made comparable

22. Detailed information on the calibration of the disease parameters is available as part of our online documentation.

to official case numbers. Secondly, individuals with undetected or not yet detected infections are an important driver of the pandemic.

In principle, our modeling approach is flexible enough to incorporate mechanistic test demand, allocation and processing models. However, there is not enough data available to calibrate such a mechanistic model.

Therefore, we aim for a simpler model of PCR and rapid tests that can be calibrated with available data on test demand and availability and – nevertheless – can produce a share of undetected cases that varies over time and across age groups and agrees with other estimates over the time periods where they are available.

PCR tests are modeled since the beginning of the simulation and determine whether a infections is officially recorded. Rapid tests are only added at the beginning of 2021. Positive rapid tests do not enter official case numbers directly, but most people with a positive rapid tests demand a confirmatory PCR test. However, positive rapid tests can have a strong effect on the infection dynamics because they trigger contact reductions and additional rapid tests.

During 2020 people can demand PCR tests either because they have symptoms or randomly. The probability that a PCR test is performed in each of the two situations depends on the number of new infections and the number of available tests. Thus, it varies strongly over time and is unknown.

To distribute the correct number of PCR tests among symptomatic and asymptomatic infections without knowing explicit test demand probabilities, we use the following approach: First, we calculate the total number of positive PCR tests by multiplying the number of newly infected individuals with an estimate of the share of detected cases from the Dunkelzifferradar project. [23] Next, we determine how many of these tests should go to symptomatic and asymptomatic individuals from data by the Robert Koch Institut. Then, we sample the individuals to which those tests are allocated from the pools of symptomatic and asyptomatic infected but not yet tested individuals.

[Janos 6]
add source

Sampling uniformly from the pool of symptomatic individuals ensures that age groups who are more likely to develop symptoms are also more likely to receive tests. Thus, the share of detected cases is much higher for the elderly than for children in time periods where many tests are done because of symptoms which is in line with the estimates from the literature.

[Janos 7]
need source

At the beginning of 2021, two challenges arise: Firstly, the externally estimated share of detected cases from the Dunkelzifferradar can no longer be used because it is based on case fatality rates which drastically change due to vaccinations. Secondly, rapid tests become available at a large scale.

We solve the first challenge by assuming that the share of detected cases would have remained at the level it reached before Christmas if rapid tests had not become

23. The Dunkelzifferradar project publishes daily estimates of the dark figure of infections under https://covid19.dunkelzifferradar.de/

available. While this is only an approximation to reality, changes in the share of detected cases that would have happened without rapid tests are very likely to be small compared to the changes caused by rapid tests.

The second challenge is solved by mechanistic rapid test demand models for the workplace, schools and by private individuals. The calibration of these models is described in Section A.6. Figure 2d shows that the number of performed rapid tests in the model fits the empirical data well (where empirical data is available).

In contrast to PCR tests, rapid tests are not perfect and can be falsely positive or falsely negative. While the specificity of rapid tests is constant over time, their sensitivity strongly depends on whether the tested individual is already infectious and if so for how long he has been infectious. Before the onset of infectiousness the sensitivity is very low (35%). On the first day of infectiousness it is much higher (88%) but still lower than during the remaining infectious period (92%). After infectiousness stops, the sensitivity drops to 50 %.

Modeling the diagnostic gap before and at the beginning of infectiousness is very important to address concerns that rapid tests are too unreliable to serve as screening devices.

We do not distinguish between self administered rapid tests and those that are administered by medical personnel. While there were concerns that self administered tests are less reliable, a recent study has found no basis for this concern.

While rapid tests do not directly enter official case numbers, many positively tested individuals confirm their rapid test result with a PCR test.. Importantly, those PCR tests are made in addition to the tests that would have been done otherwise. Section C.2 discusses the effect of rapid tests on the share of detected cases.

[Janos 8]
cite charite study on self administered tests

[Janos 9]
Need to link to data appendix once the number is there and maybe mention the number

[Klara 14]
Talk here about reactions to tests and symptoms with contact reductions. (If not here, find other place where to talk about this in detail.)

[Klara 15]
Philipp suggests to write that we choose upper bounds

B.8 Seasonality

It is widely acknowledged that the transmission of SARS-CoV-2 is subject to seasonal influences. Infectiousness is increased in winter when most contacts take place inside and the immune system is weakened by low levels of vitamin D, dry air and large temperature swings. For a detailed overview of possible drivers see Kronfeld-Schor, Stevenson, Nickbakhsh, Schernhammer, Dopico, et al. (2021).

We follow Kühn et al. (2020) and Gavenčiak, Monrad, Leech, Sharma, Mindermann, et al. (2021) in modeling seasonality in the transmission of SARS-CoV-2 as a multiplicative factor on infection probabilities. The factor follows a sine curve that reaches its maximum at January first and its minimum on June 30.

For simplicity we normalize the factor to reach one at its maximum. Thus the formula of the seasonality factor is given by:

$$s_k(t) \;=\; 1 + 0.5\kappa_k sin\left(\pi\left(\frac{1}{2} + \frac{t}{182.5}\right)\right) - 0.5\kappa_k \tag{B.1}$$

Where κ_k is difference in the seasonality factor between peak infectiousness and lowest infectiousness.

The subscript k is needed because the strength of the seasonality effect differs across contact types: Work, household and school contacts are likely to take place inside even in summer. Thus they are only subject to seasonality due to factors that influence the immune system. Other contacts (for example meeting friends and while doing leisure activities) are mostly happening outside in the summer. Therefore, transmission via those contacts should have a stronger seasonal pattern.

We calibrate $kappa_{strong}$ to 0.42 and $kappa_{weak}$ to 0.21. This is in line with Gavenčiak et al. (2021) and Kühn et al. (2020).

B.9 Initial Conditions

Consider a situation where you want to start a simulation with the beginning set amidst the pandemic. It means that several thousands of individuals should already have recovered from the disease, be infectious, symptomatic or in intensive care at the start of your simulation. Additionally, the sample of infectious people who will determine the course of the pandemic in the following periods is likely not representative of the whole population because of differences in behavior (number of contacts, assortativity), past policies (school closures), etc.. The distribution of courses of diseases in the population at the begin of the simulation is called initial conditions.

To come up with realistic initial conditions, we match reported infections from official data to simulated individuals by available characteristics like age and geographic information. The matching must be done for each day of a longer time frame like a month to have individuals with possible health states. Then, health statuses evolve until the begin of the simulation period without simulating infections by contacts. We also correct reported infections for a reporting lag and scale them up to arrive at the true number of infections.

B.10 Estimated Parameters

[Klara 16]

Philipp suggests to write more about identification. Both in general and to take seasonality as an example of how we identify both calibrated and estimated parameters.

We estimate parameters that cannot be calibrated outside of the model with the method of simulated moments (McFadden, 1989) by minimizing the distance between simulated and observed infection rates and fatality rates (disaggregated by region and age groups). Since our model includes a lot of randomness, we average simulated infection rates over several model runs.

We fit our model to data for Germany from October 2020 until June 2021. We do not use earlier periods for three reasons. Firstly, in the beginning PCR tests were highly limited and therefore it would be difficult to find good initial conditions for our simulations. In addition during the summer the case numbers were extremely low. This could lead to the epidemic going extinct in our simulation. Additionally, our model does not include international travel or other imports of cases. These would be important but difficult to model during the summer months.

To avoid over-fitting and simplify the numerical optimization problem, we only allow for five different infection probabilities: 1) for contacts in schools 2) contacts in preschools and nurseries. 3) for work contacts. 4) for households. 5) for other contacts.

We also estimate a parameter that reflects the effect of hygiene measures after November 2020 at work and in educational facilities. This parameter reduces infectiousness of contacts by one third. In total those are 10 parameters. The breakpoints the contact reduction changes are not determined from data but from announcements of policy changes. Moreover, we constrain the estimated contact reduction to follow the shape of the stringency index. The resulting contact reduction can be seen in Figure A.10

[Janos 10]
Write that the exact numbers are hard to interpret and show the infections by channel heatmap more prominently than the infection probabilities

Finally we estimate one parameter that governs the introduction of the B.1.1.7 virus variant in January 2021. This parameter implies that at the end of January roughly one case per 100 000 individuals per day is imported. After January we do not model imported cases of B.1.1.7 anymore because they are negligible compared to the endogenous growth of that virus variant.

B.11 Shapley Values

We decompose the effects of different NPIs and seasonality on the infection rates with Shapley values. Shapley values (Shapley, 2016) are a concept in game theory to divide payoffs between a coalition of players. It allows to assign a single value to the contribution of an NPI or seasonality which takes into account substitutional and complementary effects with other factors.

More formally, define a coalitional game with N players and a super-additive function ν which maps subsets of N to the real numbers. The function ν is also called the characteristic function and assigns a value to a coalition. Then, the Shapley value ϕ for player i is

$$\phi_i(\nu) = \frac{1}{|N|!} \sum_{S \subseteq N \setminus \{i\}} |S|!(|N| - |S| - 1)!(\nu(S \cup \{i\}) - \nu(S))$$

The last term $(\nu(S \cup \{i\}) - \nu(S))$ is the marginal contribution of player i minus the coalition without player i. Then, compute the sum of marginal contributions over all subsets S of N which do not include player i. Each marginal contribution has to be multiplied by all combinations of other players in S which precede i and all possible combinations of remaining players which follow player i in the coalition. To arrive at the Shapley value for player i, divide the sum by the total number of combinations.

The Shapley value has some properties.

Efficiency The sum of Shapley values is equal to the value of a coalition formed by all players.

Symmetry The Shapley does not depend on the label of a player but only on its position in the characteristic function.

Linearity The Shapley value depends linearly on the values from the characteristic function v.

Dummy Axiom The Shapley value of a player who contributes nothing to any coalition is 0.

To produce Figure 3c and Figure 3d, we calculate the Shapley values of each factor in the comparison on the cumulative number of saved infections between the main scenario and the scenario without any of the factors for every day. Then, we divide up the saved infections on a particular day according to the Shapley values for the same day which yields the daily saved infections for each factor.

Appendix C: Additional Results

[Klara 17]
Philipp suggests to do a sensitivity analysis for the seasonality

C.1 Simulated vs. Empirical Data

This compares simulated data from our model with empirical data from Germany. We look at observed infections, fatality rates, the spread of the B117 mutation, vaccinations and rapid test demands. Where available we do not only look at aggregated statistics but also analyze the model fit for age groups and federal states.

[Janos 11]
summarize the fit

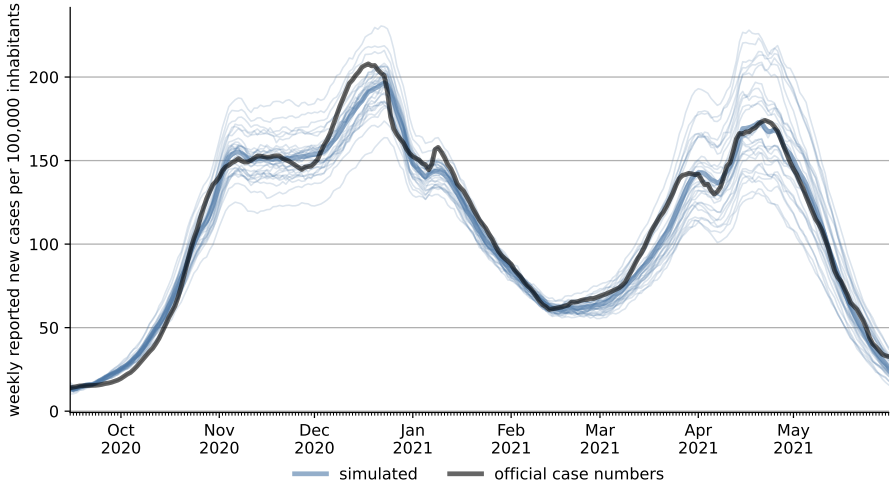


Figure C.1. Fit Over the Full Simulation Time Frame with Single Simulation Runs

Note: The figure shows the weekly incidence rates per 100,000 people for the reported simulated infections rates. The mean infection rate is the thick blue line. Single simulation runs are plotted in lighter and thinner lines. The official case numbers as reported by the Robert-Koch-Institut are plotted in black. The fit is overall very good. The higher the mean incidence and the stronger the growth the more variance there is between simulation runs. We averaged over 30 simulation runs.

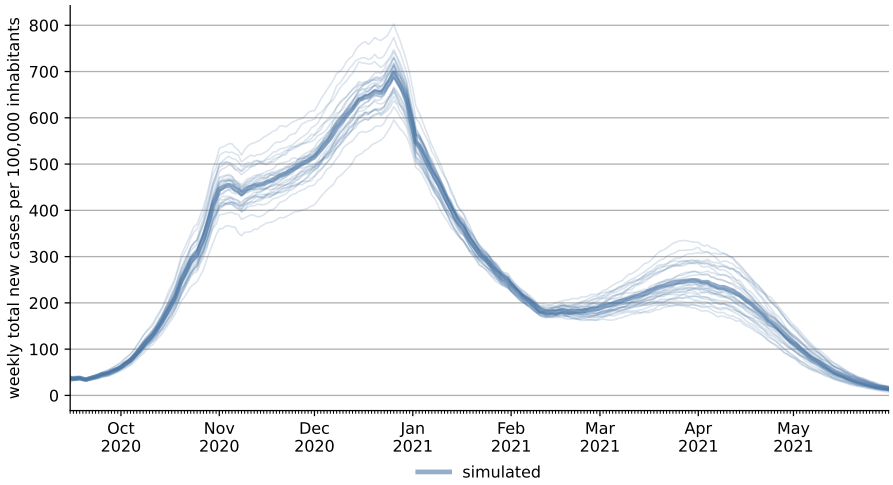


Figure C.2. Development of the Total Infections Over the Full Simulation Time Frame with Single Simulation Runs

Note: The figure shows the true weekly incidence rates per 100,000 people, including undetected cases. The mean infection rate is the thick blue line. Single simulation runs are plotted in lighter and thinner lines. The higher the mean incidence and the stronger the growth the more variance there is between simulation runs. We averaged over 30 simulation runs.

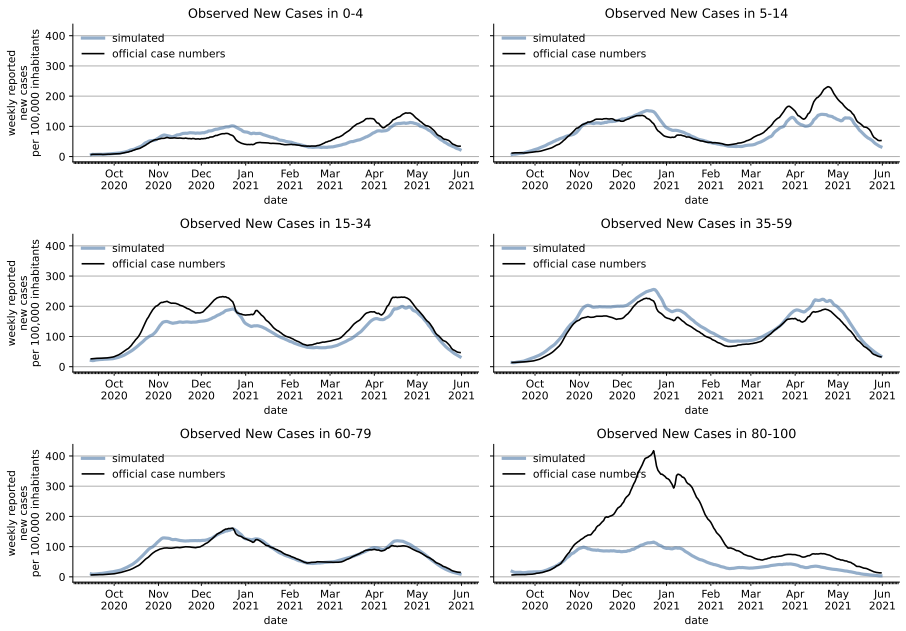


Figure C.3. Simulated and Empirical Infections by Age Group

Note: The figure shows the weekly incidence rates per 100,000 people for the reported versus the simulated infections rates for different age groups. The age group of individuals above 80 needs to be interpreted with caution because our synthetic population only includes private households, i.e. nursing homes are not represented in our model. They accounted for many cases and deaths in the winter of 2020 and many 80 to 100 year olds live in these facilities. However, the official data does not contain information on whether cases were nursing home inhabitants or not. We averaged over 30 simulation runs.

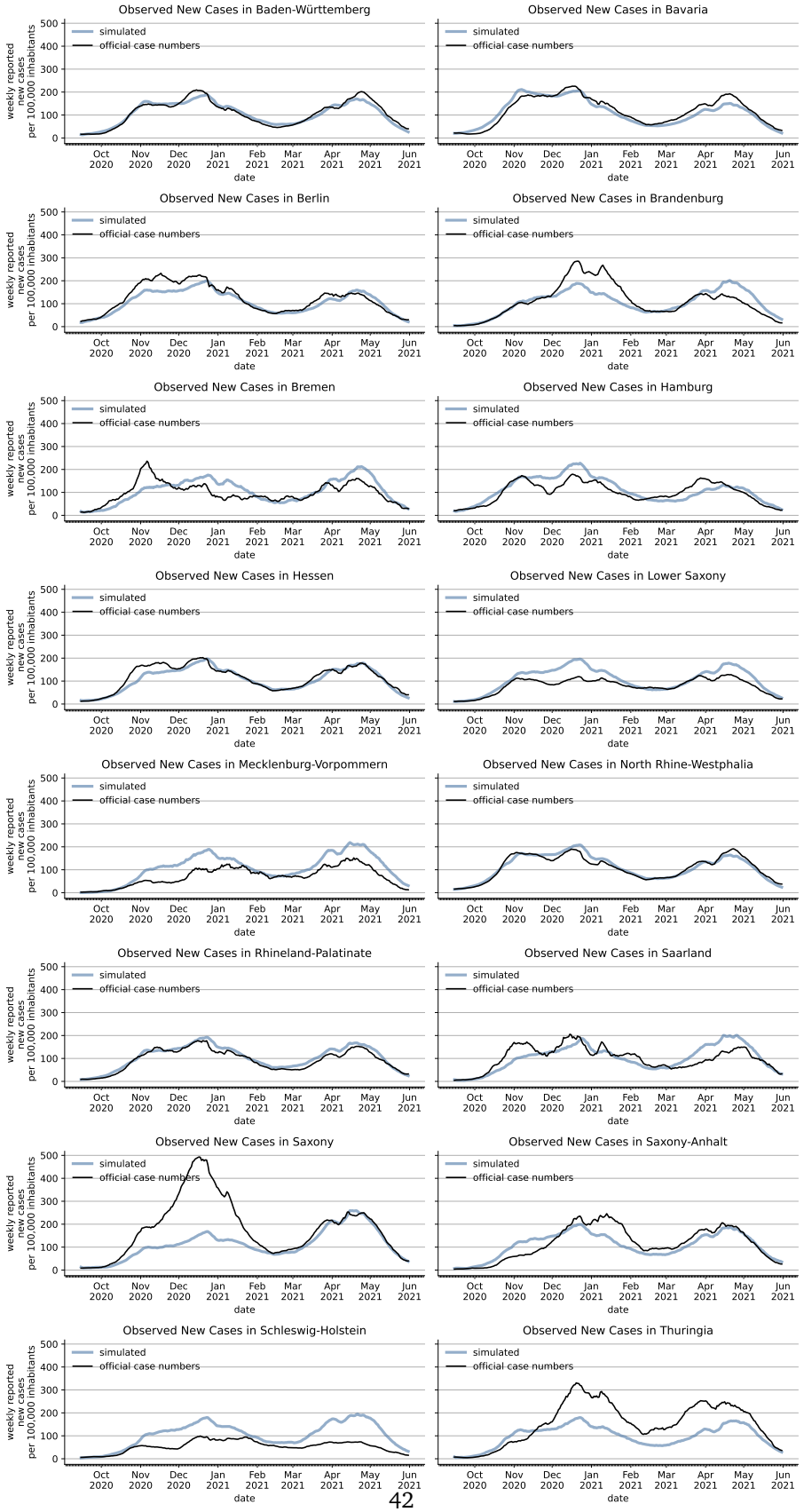


Figure C.4. Simulated and Empirical Infections by Federal State

Note: The figure shows the weekly incidence rates per 100,000 people for the reported versus the simulated infections rates for different federal states. We averaged over 30 simulation runs.

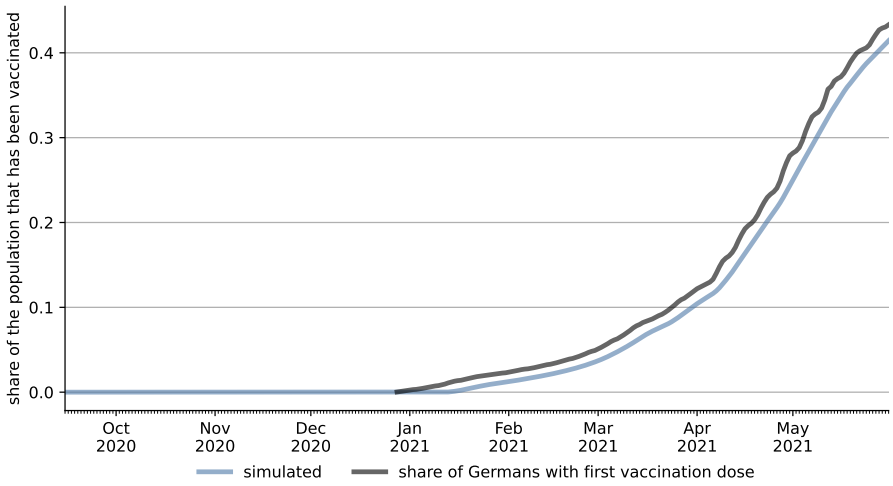


Figure C.5. Share of Vaccinated Individuals

Note: The figure shows the rate of individuals that are vaccinated in our synthetic population versus in the general German population. Note that we excluded the vaccinations that were given to nursing homes, approximately the first percent of the German population that were vaccinated. Overall, our model covers a time frame that goes from zero vaccinated individuals to a state where over 40% of the population are vaccinated. Our vaccinations work imperfectly but we do not model different vaccines nor do we distinguish between first and second shot.

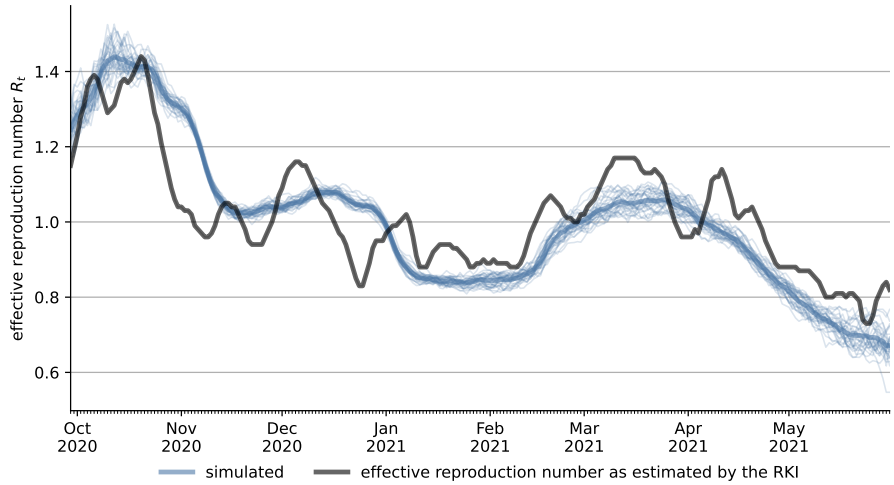


Figure C.6. Effective Replication Number R_t in the Model and as Reported by the Robert-Koch-Institute

Note: The figure shows the effective replication number (R_t) as reported by the RKI and as calculated in our model. The R_t gives the average number of new infections caused by one infected individual. The R_t in our model broadly follows the R_t reported by the RKI. Two trends stand out. Firstly, the RKI's R_t drops faster in November. This could be due to a change in the testing policy that focused tests on the elderly when the second wave hit Germany and led to a decline in the overall share of detected cases. The second difference is from mid February to mid March where the RKI's reported R_t increased more rapidly than that in our model. Here the opposite effect can be expected. During this time rapid tests increased strongly leading to more cases being detected. In the short term this leads an R_t estimation that is based on detected cases to overestimate the replication number.

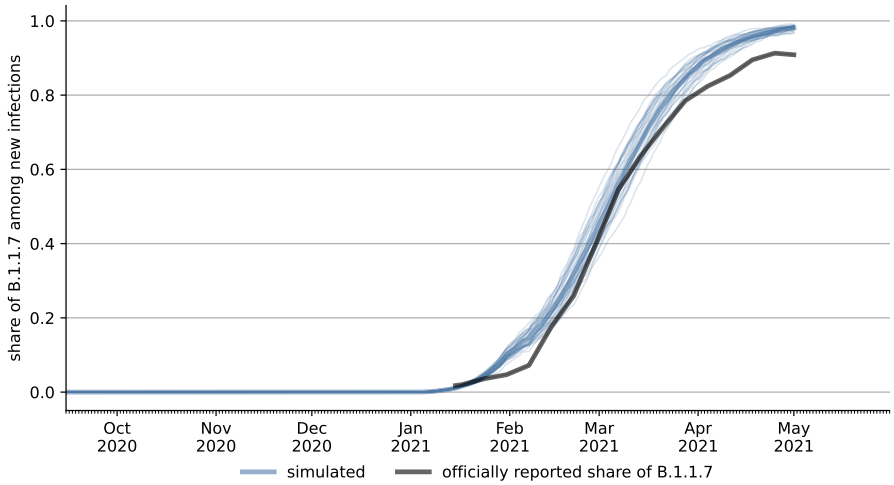


Figure C.7. Share of B.1.1.7 in the Model and as Reported by the Robert-Koch-Institute

Note: The figure shows the share of B.1.1.7 as reported by the RKI and as calculated in our model. We only introduce a few cases over the cause of January. From then B.1.1.7 takes over endogenously through its increased infectiousness. We model no other features of B.1.1.7. At most we introduce 0.75 cases per 100,000 inhabitants.

C.2 Share of Cases that are Detected

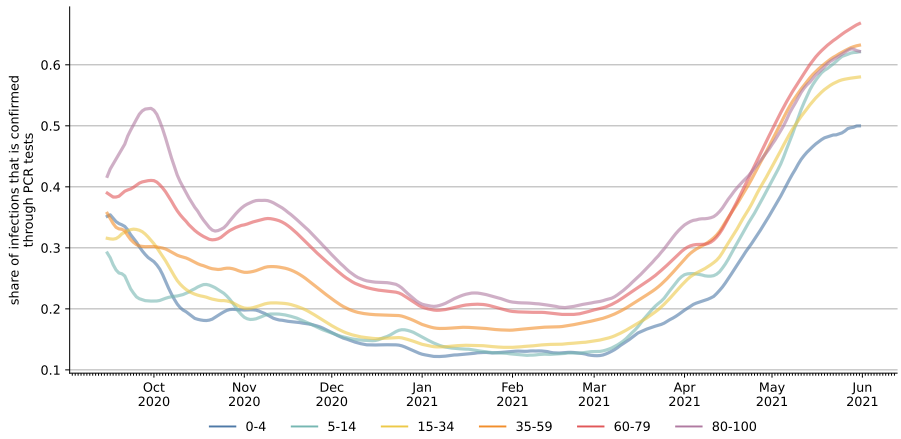
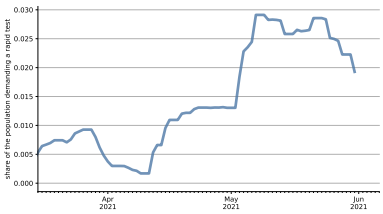


Figure C.8. Share of Detected Cases by Age Group

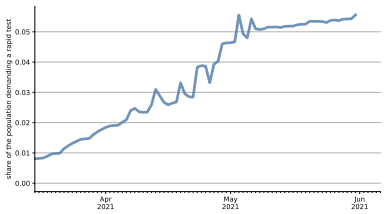
Note: The figure shows the share of cases that is reported as an official case via PCR confirmation. We use the overall share of known cases that was estimated through the case fatality ratio by the Dunkelzifferradar for all of 2020 and then assume it to be constant as vaccinations of the elderly strongly affect the case fatality rate which the project does not account for. To get from an overall share of detected cases to the share of cases that is detected in each age group we use that asymptomatic cases are much less likely to be detected. As our model covers age specific asymptomatic rates this endogenously leads to group specific share known cases that verify that infections in younger age groups are under-detected. Starting in 2021 in addition to the overall numbers of detected cases through symptoms and the share known cases, cases are also detected through confirmation of positive rapid tests. This leads to an increase in the share of known cases for all age groups but in particular for the younger age groups that are covered extensively with rapid tests through the rapid test requirement for participating in school.

It's noteworthy that the share of detected cases increases rapidly in May for the five to fourteen year olds. This is a direct result of the mandatory tests in school.

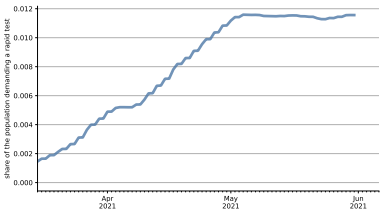
C.3 Rapid Tests



(a) Share of the Population Demanding a Rapid Test in an Education Setting



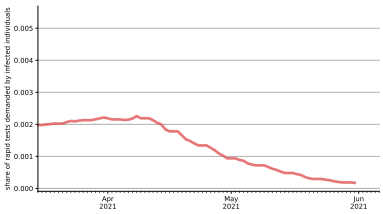
(b) Share of the Population Demanding a Rapid Test due to Work



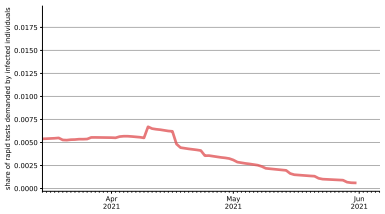
(c) Share of the Population Demanding a Rapid Test for Private Reasons

Figure C.9. Rapid Test Demand by Reason

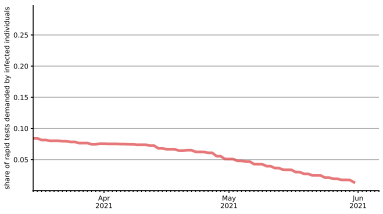
Note: Rapid tests in the education setting are demanded by teachers (nursery, preschool and school) as well as school pupils. After Easter the required frequency of tests is increased from once per week to twice per week. Work rapid tests are demanded by individuals that still have work contacts, i.e. do not work from home. The share of employers offering rapid tests increases over the time frame and the frequency of testing is also increased. Tests are demanded by individuals for one of three private reasons: having developed symptoms without access to a PCR test, having a household member that has tested positive or developed symptoms or having planned weekly meeting with friends.



(a) Share of Rapid Tests in the Educational Setting Demanded by Infected Individuals



(b) Share of Work Rapid Tests Demanded by Infected Individuals



(c) Share of Private Rapid Tests Demanded by Infected Individuals

Figure C.10. Share of Rapid Tests Demanded by Infected Individuals by Reason

Note: Rapid tests in the education setting are demanded by teachers (nursery, preschool and school) as well as school pupils. After Easter the required frequency of tests is increased from once per week to twice per week. Work rapid tests are demanded by individuals that still have work contacts, i.e. do not work from home. The share of employers offering rapid tests increases over the time frame and the frequency of testing is also increased. Tests are demanded by individuals for one of three private reasons: having developed symptoms without access to a PCR test, having a household member that has tested positive or developed symptoms or having planned weekly meeting with friends. Private rapid tests have a much higher share of infected individuals because they are mostly triggered by events that make an infection likely. Remember however, that one reason is that a household member has a positive rapid test. This means that work and education rapid tests which have a low rate of infected individuals trigger more targeted rapid tests through the household demand. They also have a much higher volume of tests. As can be seen in the decomposition (Figure 3d every category of tests is important for the overall effect. It appears that the combination of wide testing to find infection chains plus targeted tests to break those chains taking together is important.

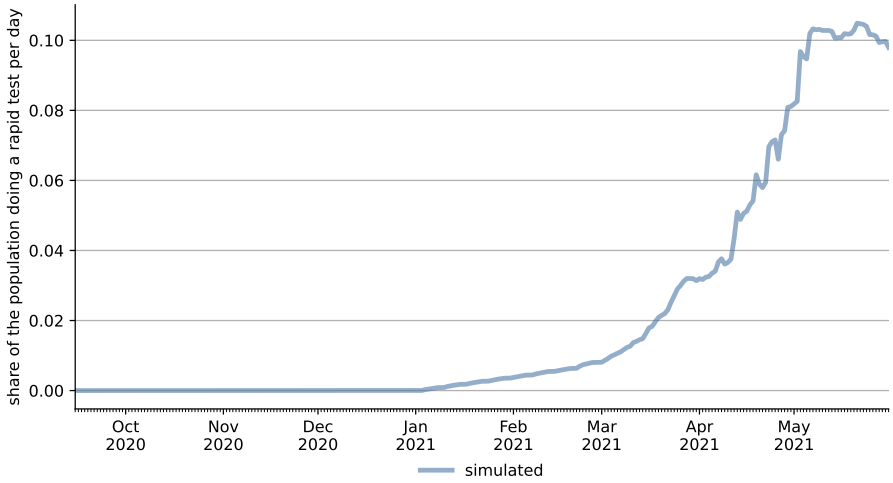


Figure C.11. Share of Individuals Doing a Rapid Test per Day

Note: The plateau in the end is the result of falling case numbers that lead to less private rapid tests being demanded due to contact tracing. The two biggest jumps are due to public holidays, i.e. the end of Easter vacations in the first half of April and May 1st. These lead many individuals to not test themselves (even though the threshold to be tested falls during the time) due to vacations from school and work. As a result more individuals than usual are due to be tested because of frequency requirements after public holidays.

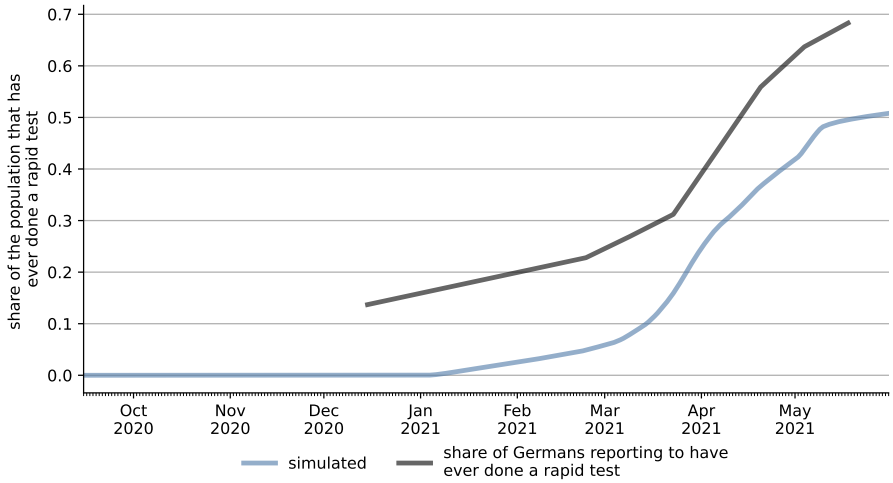


Figure C.12. Share of Individuals That has Ever Done a Rapid Test

Note: This figure clearly shows that overall our assumptions on rapid tests are conservative. In our model, the share of individuals who have ever done a rapid test lies consistently 10 percentage points below the share reported in the COSMO study (Betsch et al., 2021). The main reason for this is that we introduce rapid tests only at the start of 2021. However, using the available data to calibrate our rapid test parameters and estimating the remaining parameters to fit the official case numbers we arrive at a shape that is very similar to that implied by the survey results. This together with fitting the share of Germans with weekly rapid tests well (see Figure C.13 makes us confident that our rapid test model is a good – and especially not over-confident – representation of rapid testing in Germany.

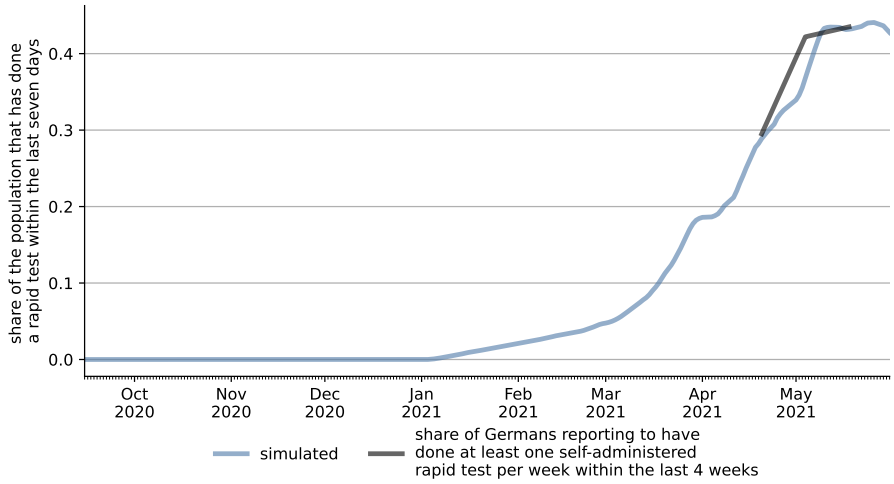
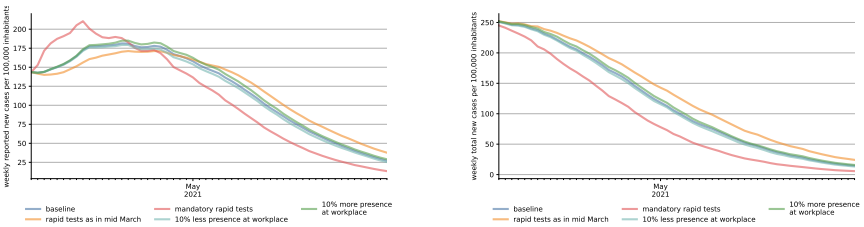


Figure C.13. Share of Individuals Who Have Done a Rapid Test in the Last Week

Note: The two lines are not perfectly compatible. The COSMO study (Betsch et al., 2021) only asked if individuals had done at least one self-administered rapid test per week in the last four weeks. This means there are two differences between the simulated line and the empirical data points. Firstly, the simulated line encompasses all rapid tests since we do not differentiate between self-administered and medically administered rapid tests. Secondly, in our model we cannot verify the rhythm over the last four weeks but just observe the last time of a rapid test. However, both work and school rapid tests which make up the largest share of rapid tests (see Figure C.9) are both required on a weekly or twice weekly basis while the private rapid test demand which are partly just triggered by events make up only a small fraction of tests.

C.4 Scenarios

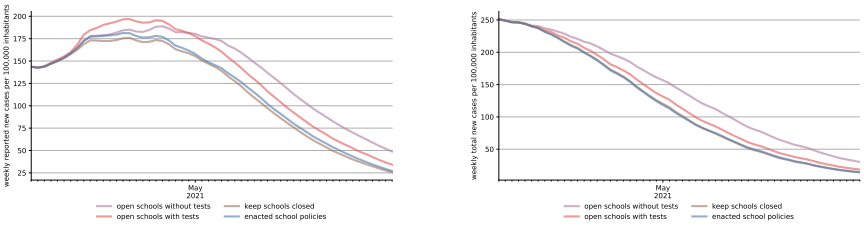


(a) Reported Cases **(b)** Total Cases

Figure C.14. The Effect of Different Work Scenarios on Reported and Total Cases

Note: The figure shows the development of cases after the policy changes took place at Easter until the end of our simulation period (end of May). We vary the share of workers that work from home and how many tests are performed at work relative to our baseline scenario. Making it mandatory to test all employees that do not work from home markedly reduces cases – even when only assuming 95% compliance on both the employer and the employee side. As before, the observed cases can be misleading because more testing leads to more detected cases. It takes two to three weeks for the reduction in new infections effect to dominate the increased detection effect. Furthermore, the two opposing effects lead to a smaller effect size than is actually the case.

[Klara 18]
Regarding figure C.14: Look up numbers and add them to the description.



(a) Reported Cases **(b)** Total Cases

Figure C.15. The Effect of Different School Scenarios on Reported and Total Cases

Note: The figure shows the development of cases after the policy changes took place at Easter until the end of our simulation period (end of May). Apart from the enacted school policies as our baseline we simulate how cases would have developed if schools had been closed completely as the strictest possible counterfactual scenario and two opening models: One where schools open normally (with hygiene measures) without any testing in the education sector and one where schools open normally but testing shares develop as in the baseline scenario. Our simulations suggest that the enacted policies were as effective as keeping schools closed. Opening schools with the testing schemes that were in place after Easter would have had a small effect on the overall incidence. However, this is mainly due to the stringent testing that was in place in schools by that time. Had schools opened without testing requirements the total incidence would have been up to 50 points higher, though this would have been less visible in the reported cases.

[Klara 19]
Regarding figure C.15: Look up numbers and add them to the description.

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