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. In order to do so, the study develops an agent-based simulation model that is estimated on 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%, large-scale 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]
Commenting is on!
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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 testing, more nuanced NPIs, and contact tracing. Neither these policies' effect nor the influence of seasonal patterns or 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

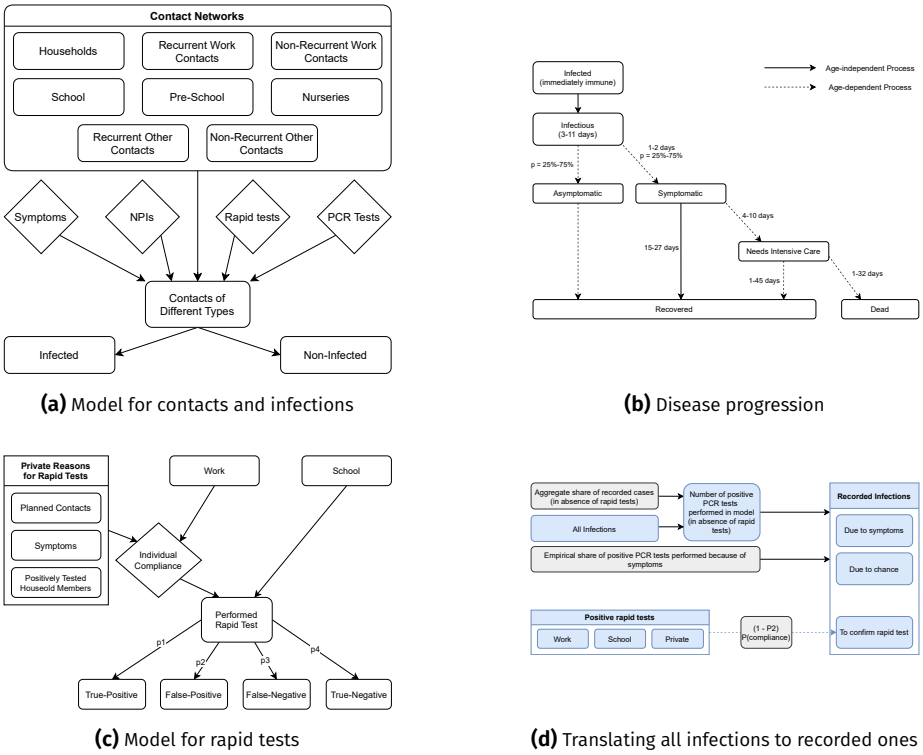
This paper develops a quantitative model incorporating these factors simultaneously. The framework allows to combine a wide variety of data and mechanisms in a timely fashion, making it useful to predict the effects of various interventions. We apply the model to Germany and show that rapid testing had the largest impact on the reduction in infections by almost 80% during the month of May 2021. We conclude that rapid tests have a large role to play 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, contacts are differentiated by age and geographical location see Section A.3 of the Supplementary Material.

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. Schools and daycare can be closed entirely, operate at reduced capacity—including an alter-

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: A description 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 avaible, agents' demand is modeled as in Figure 1c. All pupils are attending school are tested, other reasons trigger a test only for a fraction of individuals. 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.

nating 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 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 as for example also modeled in 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).

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 students to be tested regularly. Rapid tests may be offered by employers for on-site workers. Individuals may demand tests for private reasons, which include having plans to meet other people,[4] 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 offered by employers or follows up on private reasons.

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 incorporated directly from official directives. Administrative records on the number of tests, vaccinations by age and region, and the prevalence of virus strains are generally

[HM 2]

Removed "and whether she reduces her contacts if she tests positive or develops symptoms" – does not fit here. If anything, add footnote, but it seems like this is a detail that is just distracting right here. Make sure to describe clearly and at length in Appendix.

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 will make them 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.

available. Surveys may ask about test offers, propensities to take them up, and past tests.

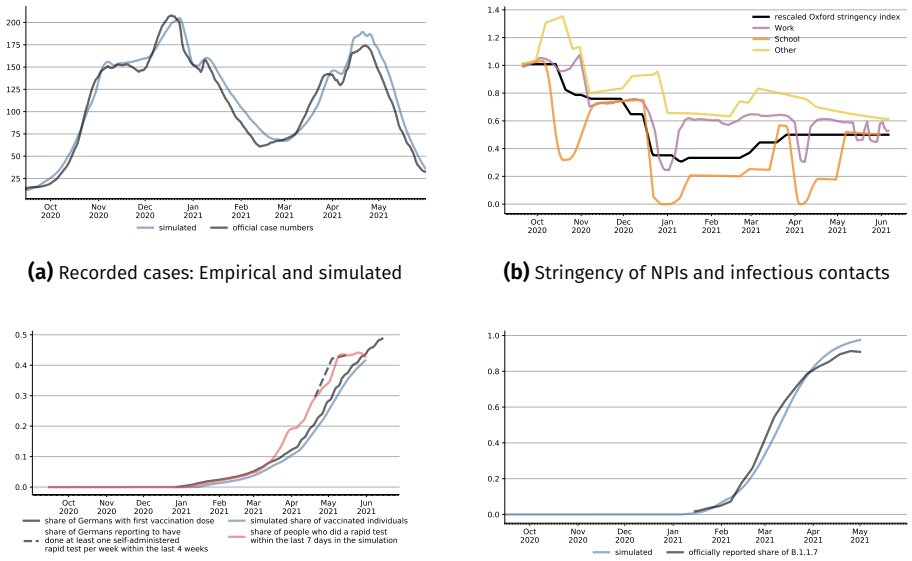
The free parameters are the infection probabilities by contact category, one hygiene multiplier for school and work contacts after November 2nd 2020, approx. ten parameters that govern the reduction of other contacts, the number of extra contacts during holidays, the share of detected cases around holidays and the fade in speed of the rapid tests as well as one parameter that governs the import of B.1.1.7 cases in January 2021. For details, see Supplementary Material B.10, A.6.

[Klara 1]
Must be updated when the estimation is finished.

We estimate these parameters such that the model matches the following empirical quantities: 1. official case numbers for each age group and region, 2. deaths, 3. share of B.1.1.7. (See McFadden, 1989, for the general method). However, only a fraction of infections actually enter the official case numbers. We thus model official cases as depicted in Figure 1d. We take aggregate estimates of the share of detected cases and use data on whether CoViD-19 symptoms led to a PCR test. As the share of asymptomatic individuals varies by age group, this gives us age-specific shares (see Figure C.4 for the share of known cases by age group over time in our model). Our estimates suggest that only 18 to 28% of cases are detected for school age children while the rate is 30 to 55% for those above age 80. Confirmation of a positive rapid test result is another reason for PCR tests, once these become available.

[Klara 2]
Must be verified once results are final.

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. For legibility, 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, which prompted 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. See Figure 2d. In early March, some NPIs were being relaxed; e.g., hairdressers and home improvement stores were allowed to open again to the public. There were many changes in details of regulations afterwards, but they did not change the stringency index.



(a) Recorded cases: Empirical and simulated

(b) Stringency of NPIs and infectious contacts

(c) Tests and vaccinations

(d) Fraction of B.1.1.7 strain

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 is 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.

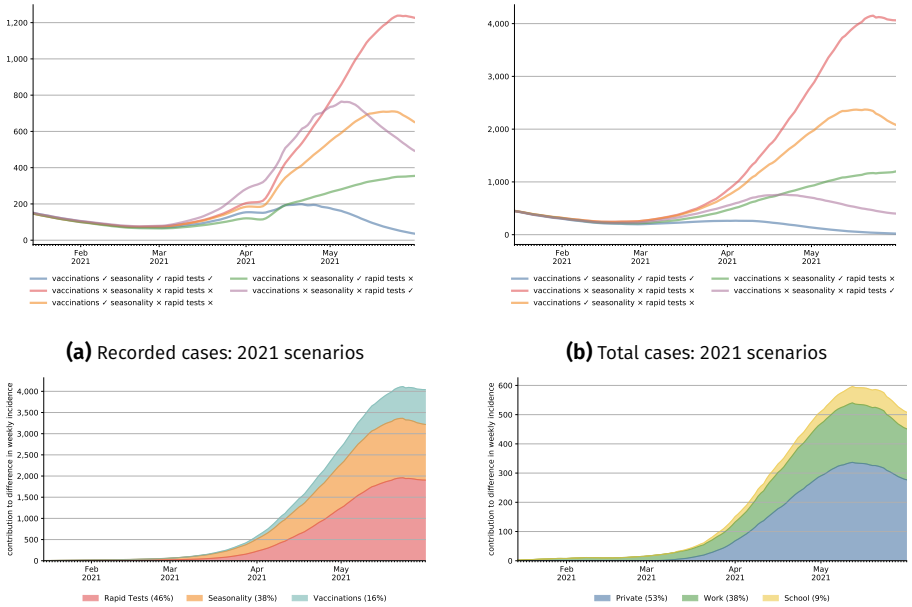
By this time, the set of policy instruments had become much more diverse. Around the turn of the year, the first people were vaccinated with a focus on older age groups and medical personnel (Figure 2c. By the end of May, just over 40% had received at least one dose of a vaccine. Around the same time, 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. Depending on the state, 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 distribution of recorded infections in September 2020 and use the model to predict recorded infection rates until the end of May 2021. See Supplementary Materials A and B for detailed descriptions of the data and the model, respectively. The blue line in Figure 2a shows 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.2 and C.3, respectively).

[Janos 2]
This needs more explanation. I will rewrite this.

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 he 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 to around 42 percent of the population, a vaccination rate that rose from 28% to 43%, and mostly seasonality impacting a fall in the relative infectiousness of contacts outside of work and school.

In order to better understand the contributions of rapid tests, vaccinations, and of 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



(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 where the individual contribution of a channel is its average contribution over different sizes of coalitions (combinations with other channels). The individual contribution to a coalition is the difference between the effect size of the coalition with the particular channel and without.

model fit (the blue line, same as in Figure 2a), a scenario without any of the three factors (red line), and three scenarios turning these factors off one by one. 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 or 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 about 15% 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

[Janos 3]

I would not mention the word "coalition" in the notes to the figure on the Shapley values. Combination with other channels is better. I think I would prefer to have a short section on shapley values in the appendix (why use them, how do they work) and just link to that in the figure note

individuals. These groups contribute less to the spread of the disease than others due to a lower number of contacts, see Supplementary Material A.4. It is important to note that the initial focus of the campaign was to prevent deaths and severe disease; 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 June). By the end of our study period, when first-dose vaccination rates reached around 40% of the population, the numbers of new cases would have started to decline.

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. Nevertheless, we estimate it to be a quantitatively important factor determining the evolution of the pandemic, explaining most of the early changes and almost 40% of the cumulative difference by the end of May.

The largest effect—almost one half when considering the decompositions—comes from rapid testing. Here, it is crucial to differentiate between recorded cases and actual cases. Additional testing means that infections are detected, which would otherwise remain undetected. Figure 3a shows that this means that until late April, recorded cases are higher than in the scenario where none of the three mechanisms are turned on. Compared to the scenario with vaccinations only, this point is reached around mid-May and it would be June for the comparison with the seasonality-only scenario. The effect on total cases, however, is visible immediately. Despite the fact that only a small fraction of the population performed weekly rapid tests in March,[6] new infections on April 1 would be reduced by 53% relative to the scenario without vaccinations, rapid tests, or seasonality.

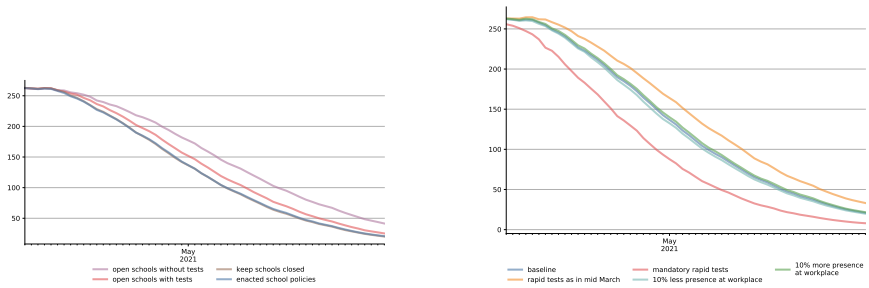
So why is rapid testing so effective? In order to shed more light on this question, Figure 3d decomposes the difference in the scenario without rapid tests only (purple line in Figure 3b) and the main specification into the three channels for rapid tests. Tests for pupils have the smallest effect, which is largely explained by the relatively small number of students (Only 18% of our population are in the education sector (pupils, teachers etc.) versus 46% are workers outside the education sector) and the fact that schools did not operate at full capacity during our period of study. 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,

[HM 3]
How many tests are actually performed along each of the three dimensions? Could this be a quantity story rather than the directed testing story I am making up here as wishful thinking?

[Klara 3]
See subsection C.3.

6. 4% to 6% have done a rapid test within the last seven days in the first week of March. 8% in the model have ever done a rapid test at that point; 27% of respondents to the COSMO study reported in early March that they *ever* did a rapid test)



(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.

Rozhnova, Bootsma, Boven, Wijgert, et al., 2020; Contreras et al., 2021). This is also the reason for why the number of tests performed fall at the very end of our study period. Falling infection rates mean that there are fewer events triggering private test demand.

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 capacity with increased hygiene measures, before being closed again from mid-December on. Some states started opening them gradually in late February, but usual operation was not back 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 7% 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 0.017 and 0.045, 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 socio-economic 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 no test strategy is available, trade-offs may well be different.

Figure 4b shows that with a large fraction of employees receiving tests, testing at the workplace has larger effects than changing requirements to work from home. Whether the share of workers working at the usual workplace is reduced or increased by ten percent hardly has an effect on infection rates. Making testing mandatory

[HM 4]
Positive rates along the three channels might be nice here, if previous comment is not a quant story

[Klara 4]
See figure 4a

[HM 5]
I think there is a story in here about risk conditional on past exposure vs. prospective risk in gatherings, but it is too late to work through it. We might just want to calculate the probabilities.

[Klara 5]
I don't understand which probabilities you mean.

[HM 6]
Need a back-of the envelope calculation

[HM 7]
need to cite a couple of poor learning outcomes / mental health papers. There must be well-published ones

[Klara 6]
I googled and found two that I think are at least not terrible but I also didn't find anything really well published

twice a week—assuming independent compliance by employers and workers or 95% each—would have reduced infections by 13%. Reducing rapid tests offers by employers to the level of March would have increased them by the same amount.

Despite these large effects, the results on testing likely understate the benefits. Disadvantaged groups of the population are less likely to be reached by testing campaigns; at the same time they have a higher risk to contract CoViD-19.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.

Our analysis has shown that in the transition path 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 day of the winter lockdown in Germany is estimated to have cost 6.25 billion Euros (Dorn, Fuest, Göttert, Krolage, Lautenbacher, et al., 2020). In early June 2021, retail prices for self-administered rapid tests are frequently less than 1 Euro.

[HM 8]
seems obvious, but I did not find anything. COSMO data? We should get the raw data, btw.

[Janos 4]
The conclusion should be slightly longer and more separated from the rest

[Klara 7]
This is a prediction by the ifo Instute back from March 2020 assuming a 2 month lockdown. I did not find anything citable that is more recent. I did find A quote from Ifo's Timo Wollmershäuser: „Wir liegen zwischen zwei bis zweieinhalb Milliarden Euro pro Woche" for the winter lockdown

[HM 9]
Cheapest on Amazon on June 11th, 2021. — DM 95ct

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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.

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,

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

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).

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% 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 8]
To be written

A.3 Number of Contacts

[HM 10]
Histograms seem like the way to go here. Also add household contacts, i.e., distribution of (household size minus 1).

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 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.

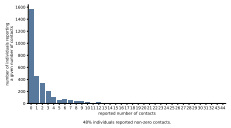
[Klara 9]
Put plots into one figure.

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 on which we build our synthetic population we simply assume for the household contact model that individuals meet all other household members every day.

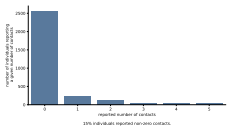
[Klara 10]
Cite microcensus

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).

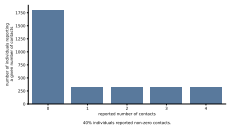
10. The length of symptoms is not very important in our model given that individuals mostly stop being infectious before their symptoms cease.



(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.

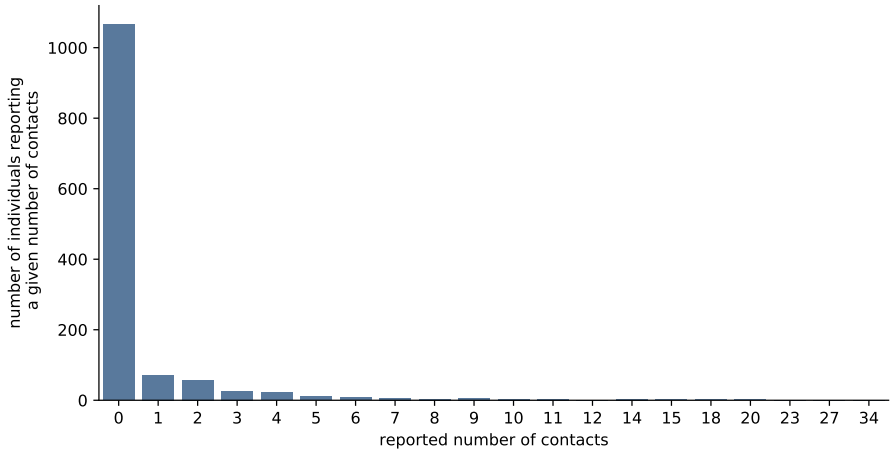


Figure A.2. Number of Non Recurrent Work Contacts

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.

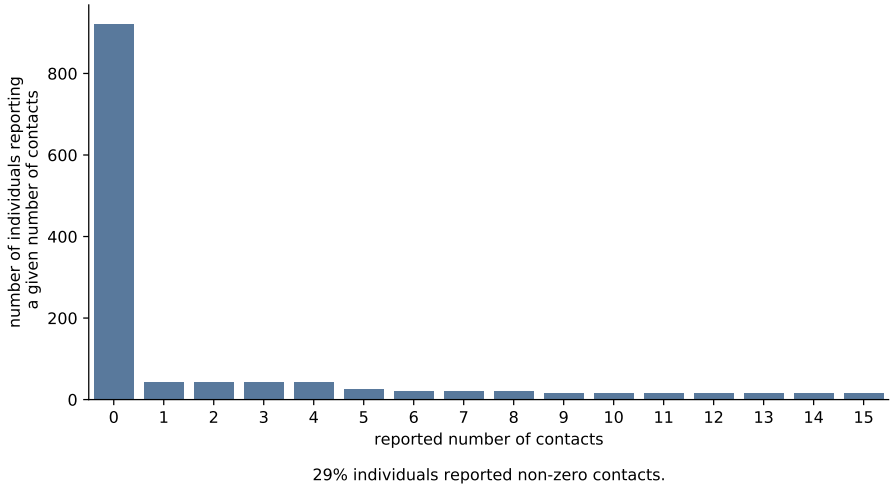


Figure A.3. Number of Daily Recurrent Work Contacts

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.

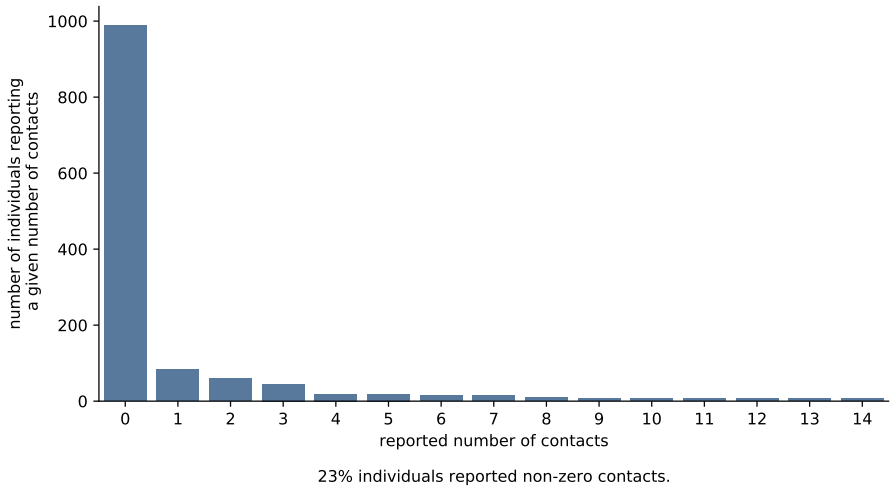


Figure A.4. Number of Weekly Recurrent Work Contacts

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.

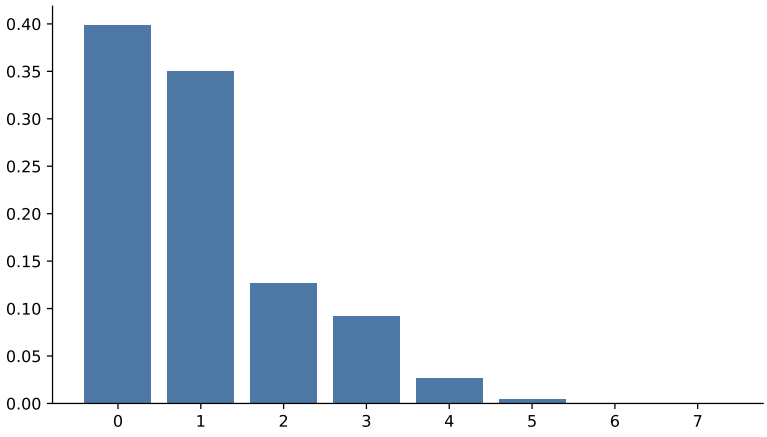


Figure A.5. Number of Household Contacts

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.6, 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 11]
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

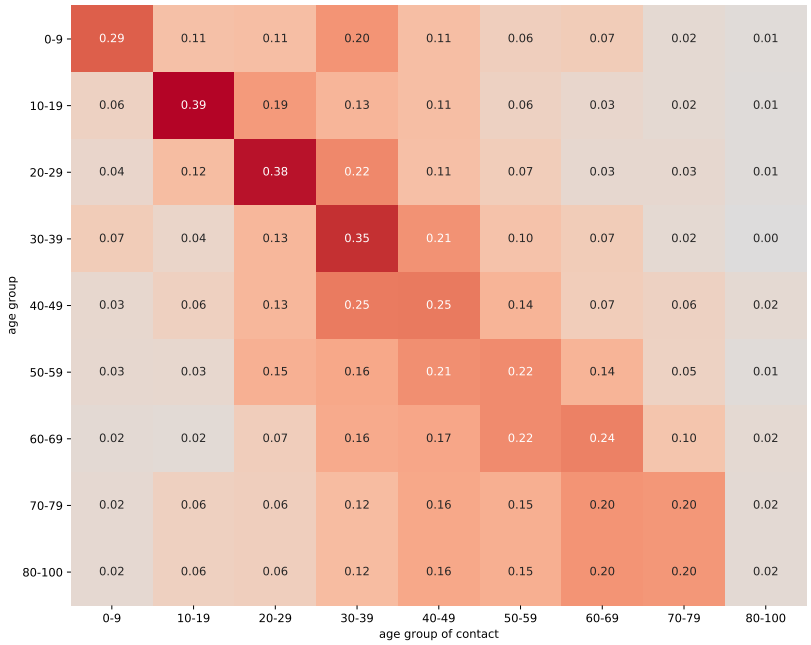


Figure A.6. Distribution of Non Recurrent Other Contacts by Age Group

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

[HM 12]
So no work in here? How about school? Can we add a column with marginals and another one with work / (school?), too?

[Klara 11]
I hope adding work and writing about school and households addresses all questions. I think marginals would be confusing because they may not add up to one given that age groups have different group sizes.

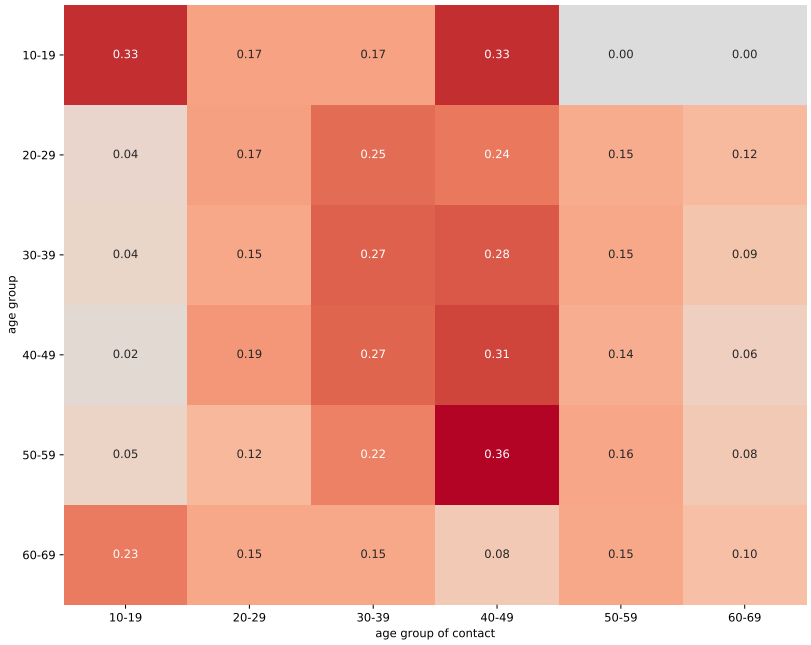


Figure A.7. Distribution of Random Work Contacts by Age Group

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.

A.5 Policies and Seasonality

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 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

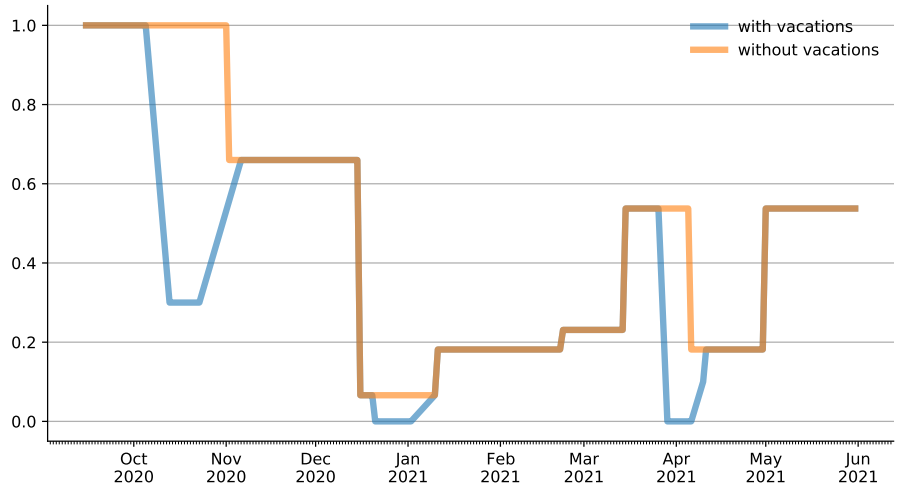


Figure A.8. School Multiplier With and Without Vacations Factored In

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

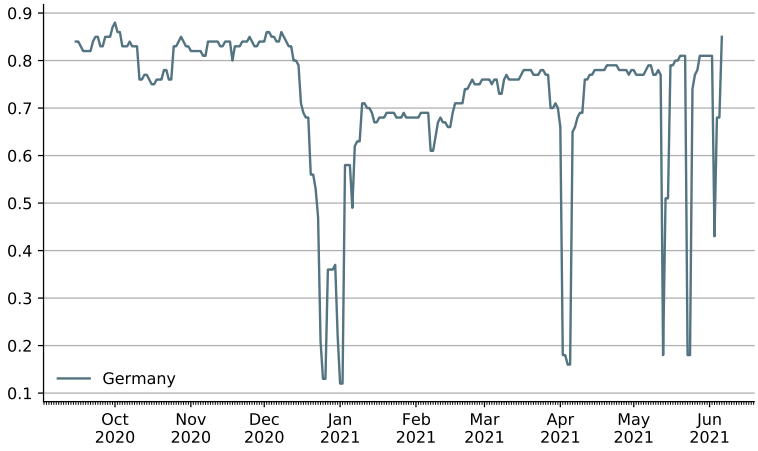


Figure A.9. Share of Workers with Work Contacts

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 by German state to determine which workers go to work depending on the state they live in.

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).

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.

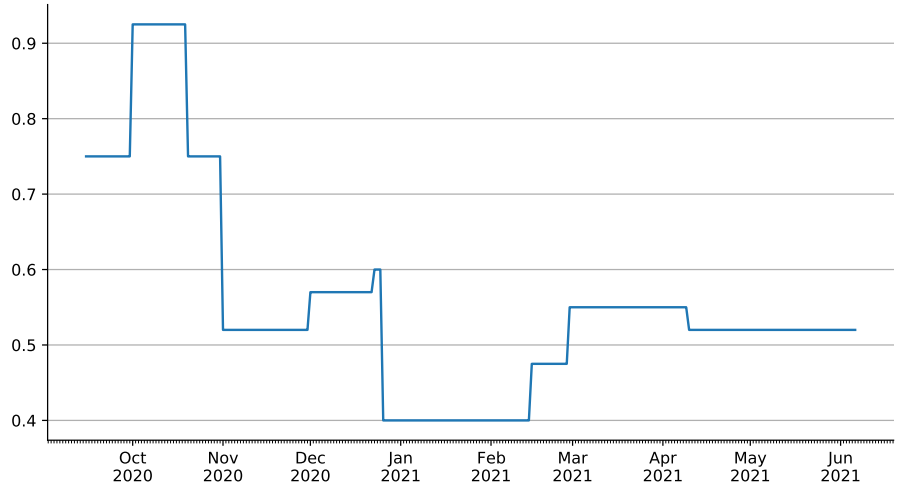


Figure A.10. Share of Other Contacts Still Taking Place

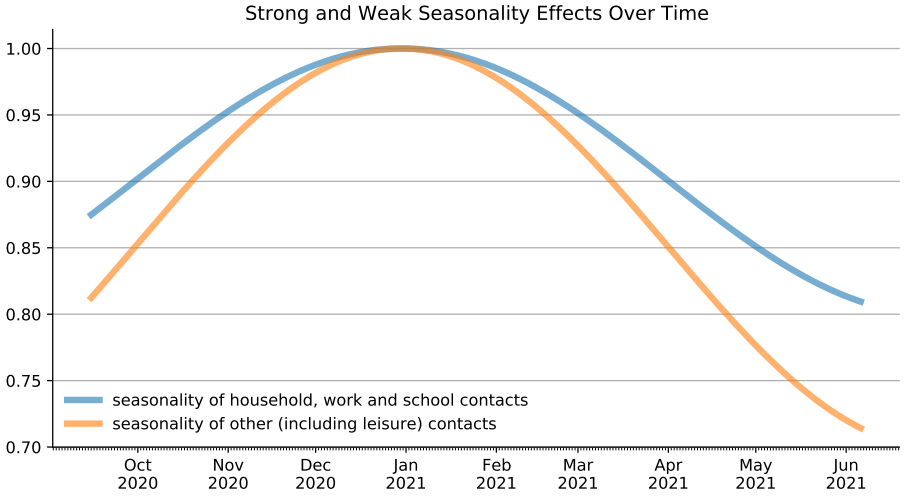


Figure A.11. Seasonality by Type of Contact

A.6 Rapid Test Demand

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

[Janos 5]
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)

(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

A.6.1 work rapid tests. 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 12]
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.

A.6.2 educ rapid 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

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

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]

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 6]

Talk about the interpretation of each line.

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

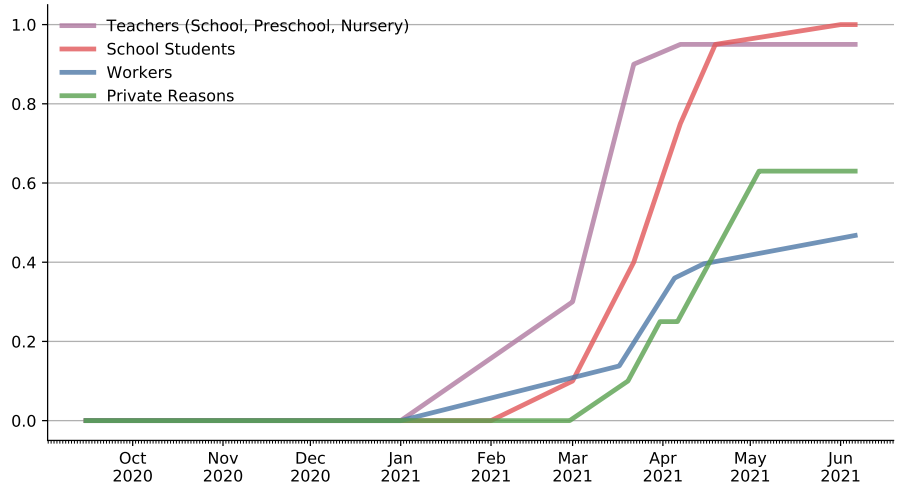


Figure A.12. Share of individuals who do a Rapid Test.

...

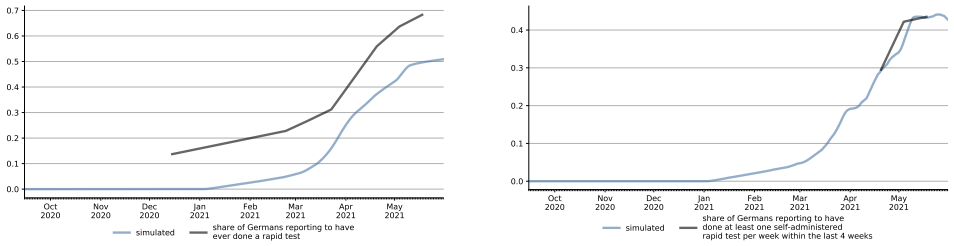


Figure A.13. Share of Individuals With Rapid Tests

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

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 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.

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.
- 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.

[HM 14]

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 (?), ...

- 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.

reduce the number of free parameters and thus avoid a potential over-fitting we only estimate different infection probabilities for the areas work, school, preschool and nurseries, households and other contacts.

B.4 Reducing Numbers of Contacts Through Policies

The main motivation of our model is to predict the effect of policies that affect the number of contacts people have. Examples range from school closures and lockdowns to more nuanced policies such as mandatory quarantines for symptomatic individuals or a class splitting policy where only half of the students come to school in person and the other half joins digitally with weekly rotation.

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 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. For example, school closures simply set all school contacts to zero. A lockdown where only essential workers are allowed to work means that approximately two thirds of the working population have zero work contacts and the rest has the same number of contacts as before.

This, in conjunction with our fine-grained contact types, allows us to easily implement a wide variety of policies. Allowing policies to depend on the health states of the entire population means that adaptive lockdowns where, for example, schools close when a certain threshold of infections is surpassed at the county level would be as simple as determining which counties are above the threshold and then setting all school contacts in these counties to zero.

The dependency of policies on health states also makes it possible to model contact tracing. For example, a policy could check whether each child has a classmate who's received a positive test result and then bar all children of that class from attending school.

Some policies can be easily implemented if the background characteristics are suitably extended. For example, a schooling policy of splitting and rotating classes, where each half attends school every other week can be implemented by storing whether the child would attend in even or odd weeks in the background characteristics and then using that information in the policy function.

For some policies the exact effect on each contact type is not easy to determine. If this refers to a policy 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. If instead it refers to a policy that we want to simulate, we make a scenario analysis in which the model is simulated with several assumptions about how the policy affects the number of contacts.

B.5 Endogenous Contact Reductions

Policies are not the only way in which the number of contacts are reduced compared to the pre-pandemic level. It is important to model those other channels. Otherwise, the effect of policies would be overestimated and policy recommendations based on the model would be biased.

Examples of endogenous contact reductions are manifold: symptomatic people stay at home; Members of risk groups try to reduce their number of contacts more strongly than others; People self-isolate if they know they had a risk contact.

Since we model the number of contacts as arbitrary functions of background characteristics and health states, it is easy to implement such considerations.

In our current empirical application we only model that symptomatic people reduce their number of contacts across all contact types (except for households) by 70 %. Within households they reduce contacts by 50%. We are working on extending this to allow for formal and informal contact tracing as well as quarantines after positive test results. 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.6 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 our 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 variable in the background characteristics. An example would be a school class identifier which could come from actual data or be drawn randomly to achieve representative class sizes. 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.5 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 seems like 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).

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.

Below, we first show pseudo code for the non-recurrent matching algorithm and then describe how the algorithm works in words.

We first 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. This has 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

```
while are_unmatched_contacts_left:

    contact_type, i = draw_contact_type_and_individual()

    for _ in remaining_contacts[i, contact_type]:

        group_j = draw_group_of_other_person()
        j = draw_other_person_from_that_group(group_j)

        if infection_takes_place(i, j):
            update_health_state_of_freshly_infected()

        remaining_contacts[i, contact_type] -= 1
        remaining_contacts[j, contact_type] -= 1
```

Listing 1. Pseudo-code of the matching algorithm for non-recurrent contacts.

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

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 increases quadratically in the second stage group size.

B.7 Course of the Disease

The following medical parameters describing the progression of the disease are taken from systematic reviews (e.g. He et al. (2020)). After an infection occurs, the disease progresses in the way depicted in Figure 1b.

First, infected individuals will become infectious after one to five days. 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 or demand a test and 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 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[21] and age-dependent.

B.8 Testing

Our model includes both PCR tests which are scarce and take time until the result becomes available and rapid tests which are done after an individual's contacts are determined but before the contacts take place.

PCR testing consists of three stages. Firstly, we model who demands a PCR test. Demand functions map from individual characteristics to a probability which is the probability for this individual to demand a test. There can be multiple demand functions where each function may describe a different channel. For example, individuals who experience symptoms or have a risk contact may ask for a test. Or, the ministry of education requires a negative test result from every teacher every second week. After the probabilities for each individual and every demand model are computed, individuals who demand a test as well as the channel is sampled.

The second stage is the allocation phase in which demand and supply for tests are matched. The number of available tests can be inferred from official data and used to model shortages in supply. When demand exceeds supply, some individuals might be given preferred access to tests because of their own vulnerability or their potential to become a super-spreader.

In the last and third phase, administered tests are processed. This step can become a bottleneck in the testing process if there are not enough laboratories or necessary resources available to evaluate all tests.

In our empirical estimation we use a very simplified testing model where the number of tests to be distributed is calculated from estimates for the ratio of known to all infections.[22] Using these estimates as well as data on the test distribution over age groups by the RKI[23] we allocate tests firstly among the symptomatic and then randomly allocate tests to newly infected to fit the German test distribution.

[Janos 7]

To Do für Appendix an der Stelle: Institutional details:

- PCR tests only at doctor's office / test centers.
- Fraction PCR tests performed because of contact with infected people is small (quarantine mandate more common) – need citation
- Rapid tests available in many pop up test centers, self-administered tests in every drug store / supermarket, prices in early June < 1 Euro

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

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

23. https://ars.rki.de/Content/COVID19/Main.aspx

Rapid tests are modeled much simpler. Every day before individuals have contacts they can decide to be tested. For example students that plan to attend school that day and have not done a rapid test in the last three days get a rapid test. Then they immediately receive the test result. After they have received their test result individuals can react to it by reducing their contacts. For example positively tested individuals may not go to work and reduce their household contacts to some degree. Who reduces their contacts to what degree depends on a quarantine compliance attribute.

[HM 15]
If we get econ readers, we should not use language like this because we do not have a choice model.

Our rapid tests include false positives and false negatives. The sensitivity of rapid tests in our model depends on when the individual has or will become infectious. This way we can account for the fact that rapid tests are likely to be false positive before infectiousness starts.

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

We estimate parameters that could not be calibrated inside the model with the method of simulated moments (McFadden, 1989) by minimizing the distance between simulated and observed infection rates. Since our model includes a lot of randomness, we average simulated infection rates over several model runs.

We use 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.

Table B.1. Estimated Infection Probabilities

Contact Type	Infection Probability
preschool and nursery	00.500%
school	01.200%
household	10.000%
work	14.500%
other	15.875%

Notes: School contacts take place Monday through Friday. All students and teachers meet all other students and teachers that attend school that day and there are three classes taking place each day. Work contacts can be daily, weekly or non recurrent. Other contacts can be daily, weekly or non recurrent. We do not differ the infection probability depending on how often a contact takes place.

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 probabilities: 1) for contacts in schools 2) contacts in preschools and nurseries. 3) for work contacts. 4) for households. 5) for other contacts.

The infection probabilities estimated from our model are as shown in Table B.1.

[Klara 13]
Missing to add data for the other estimated parameters (import of b117 etc)

[Klara 14]
Update table after the new estimation is finished

[Janos 8]
Further things:

- talk more in detail about vaccinations? (35% reach immunity after two weeks, 40% after three weeks, distribution with the STIKO groups and children and youths...)

[Janos 9]
summarize the fit

[HM 16]
Also need to show simulated total infections somewhere. So far only ever shown for 2021.

Appendix C: Additional Results

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.

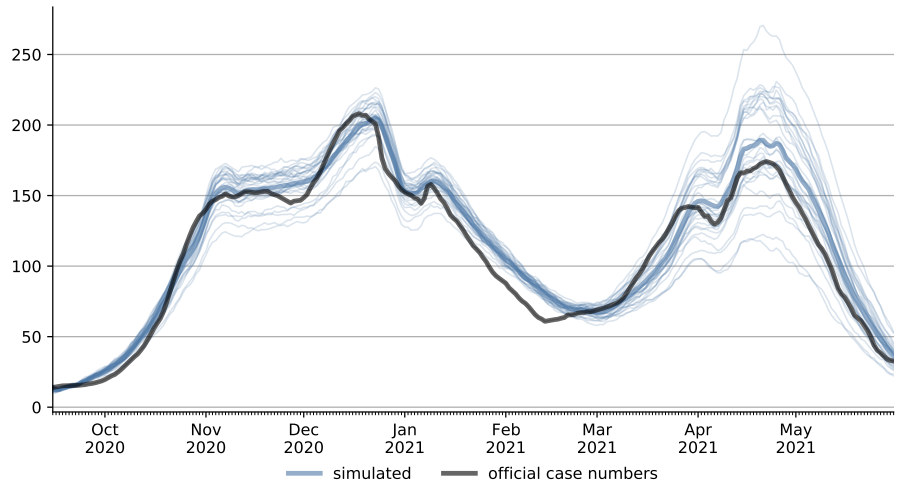


Figure C.1. Simulated and Empirical Infections

Notes: The figure shows the weekly incidence rates per 100,000 people for the reported versus the simulated infections rates.

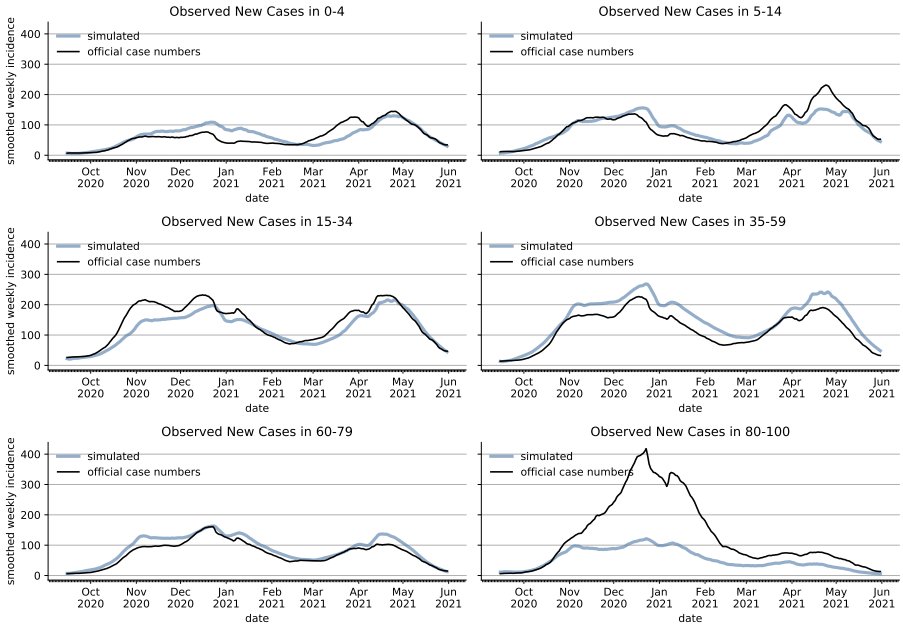


Figure C.2. Simulated and Empirical Infections by Age Group

Notes: The figure shows the weekly incidence rates per 100,000 people for the reported versus the simulated infections rates for different age groups.

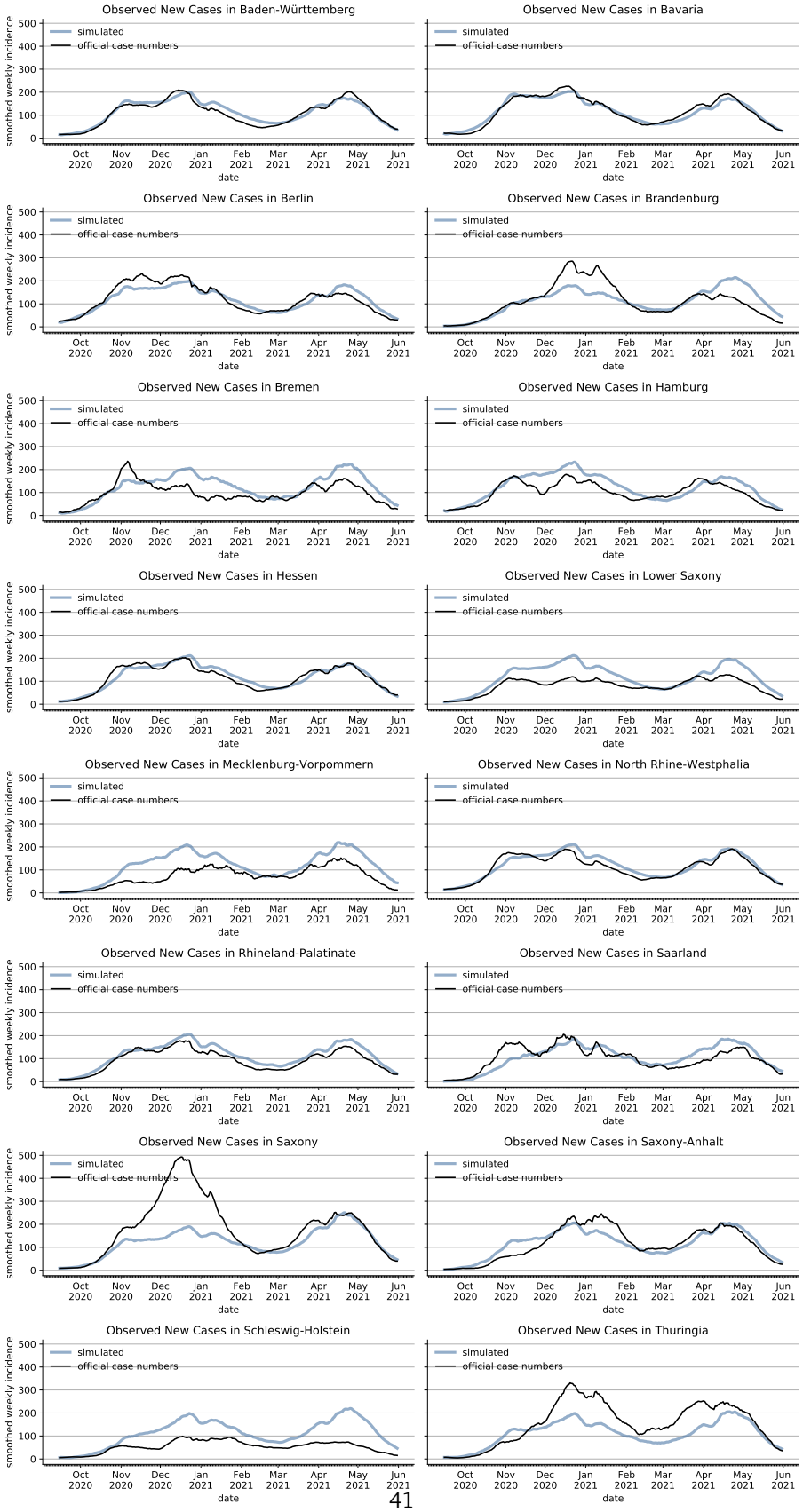


Figure C.3. Simulated and Empirical Infections by Federal State

Notes: The figure shows the weekly incidence rates per 100,000 people for the reported versus the simulated infections rates for different federal states.

C.2 Share of Cases that are Detected

[Klara 15]
Figure notes missing

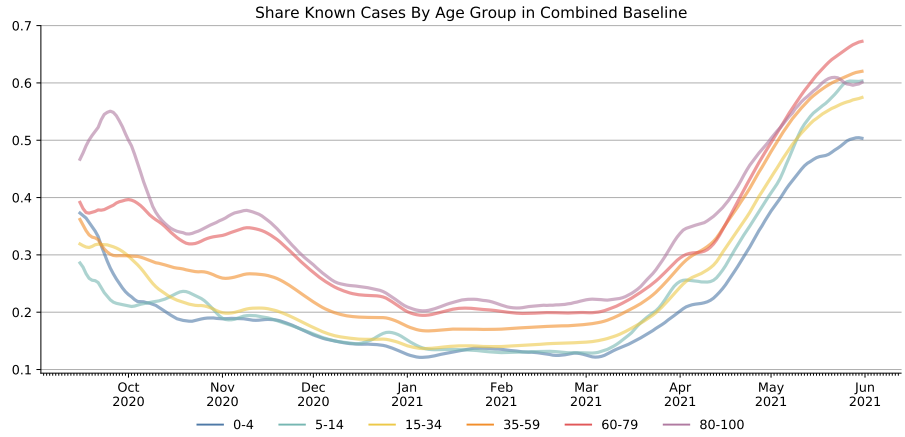


Figure C.4. Share of Detected Cases by Age Group in the Main Prediction

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

[Klara 16]
The figures will likely change layout later

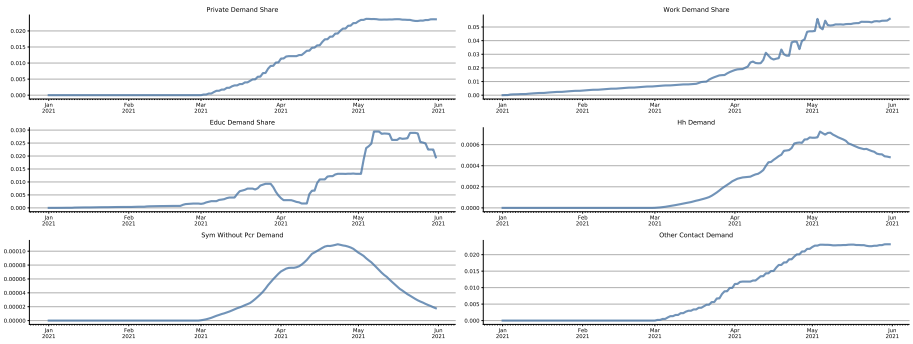


Figure C.5. Share of the Population Demanding a Rapid Test for a Particular Reason

Note that the lower three (household demand, symptomatic without PCR demand and other contact demand together form the private demand category. Also note that these do not add up to the total share of demanded rapid tests as individuals may have more than one reason to demand a rapid test on any given day.

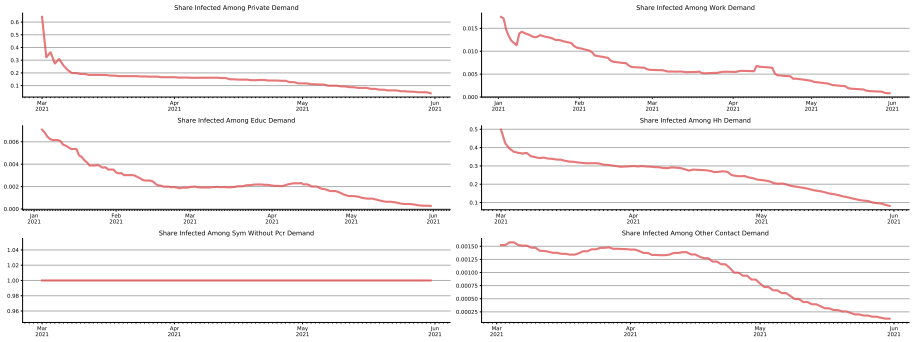


Figure C.6. Share of individuals who Demand a Rapid Test for a Particular Reason that are Actually Infected

Note that the lower three (household demand, symptomatic without PCR demand and other contact demand together form the private demand category. Also note that this is not the same as individuals getting a positive rapid test. The sensitivity is quite low before individuals become infectious. Therefore, if individuals are still in the latent period of their infection they are likely to get a false positive rapid test.

C.4 Scenarios

This is the results section.

[Klara 17]

The results can be found in 'lts'. This includes and tables for lookup and summary tables.

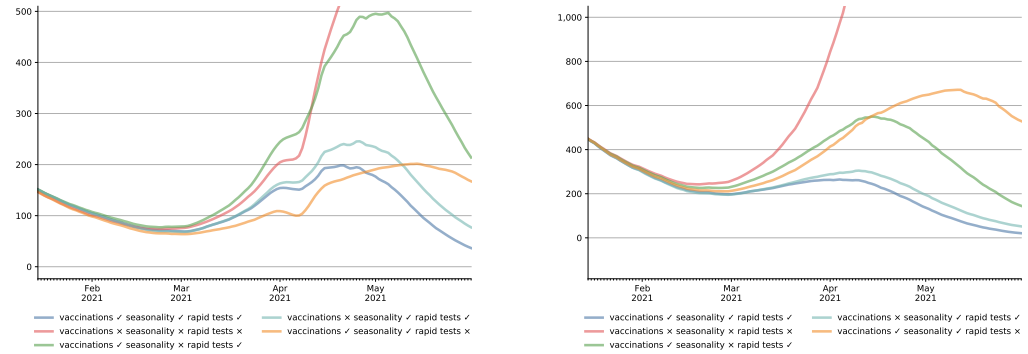


Figure C.7. The Effect of Policies on Observed and Unobserved Cases

Notes: ...

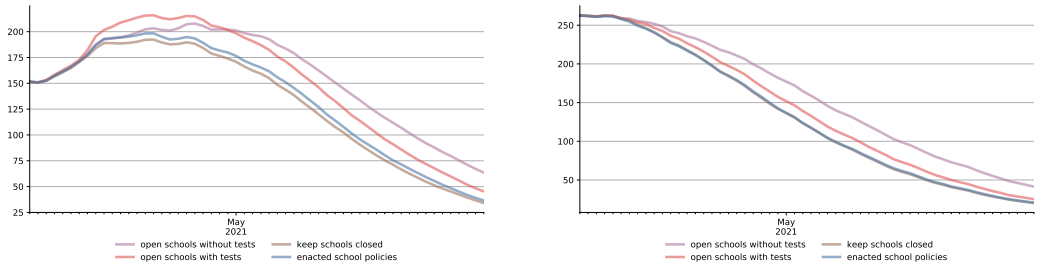


Figure C.8. The Effect of Different School Scenarios on Observed and Unobserved Cases

scenario	predicted total infections among 5-14 year olds from Easter until 2021
educ open after easter without tests	8
educ open after easter with tests	6
close educ after easter	4
baseline	4