Facemasks and COVID-19 case fatality rate

by

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Acknowledgments

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Abstract

The importance of facemasks during COVID-19 pandemic has been a controversial topic. However, many countries worldwide have already issued mask mandates. Here I show, that counties with mask mandates in Kansas during the summer of 2020 had a significantly higher case fatality rate compared to Kansas counties without mask mandates, with a risk ratio of 1.85 for death with COVID-19.

Even when correcting the for the number of 'protected people', this is the number of people that were *not* infected in the mask mandates group compared to the no mask group, the risk ration remains highly significant at 1.52.

Over 95% of this effect can solely be attributed to COVID-19.

Why this happens and the possible connection between long-term effects associated with SARS-CoV-2 and facemasks are explained in theory herein by the 'foegen effect', which describes the deep reinhalation of pure virions that were caught in the facemasks as droplets.

Introduction

The COVID-19 pandemic has caused many countries in the world to issue mask mandates.

A lot of focus has been put on the question whether mask mandates reduce infection rates, some studies showing a reduction[1], others not succeeding in proving a protection for the wearer[2].

A lot less focus has been put on the course of the disease under mask mandates. However, the important question should always be "how many lives can be saved", not "how many infections can be prevented".

There is a common concept that the severity of the disease is dependent on the number of virions transmitted, and that masks reduce that number and thus the severity of the disease is reduced[3,4]. This would result in a lower case fatality rate (CFR).

The opposite of the above concept, an unproven hypothesis, would be that by inhibiting the clearance of virions from the respiratory tract, the facemask might actually worsen the disease, which would increase the CFR. While that sounds far-fetched at first glance, there are some hints in the literature that might actually point that way.

An improved clearance by use of mucoactive agents has been proven against placebo to be successful many times, be it herbal medicine[5] that has been used for centuries, or newly developed pharmaceutical drugs[6,7].

There are also observations during the ongoing COVID-19 pandemic that hint this direction, like the many deaths among medical personnel e.g. in Italy dying during the "first wave" of the pandemic[8] – they were working many hours, despite being ill, and with facemasks.

While one might think that obstructing the exhalatory pathway in respiratory infections has never been done before, this is actually done regularly when patients develop acute respiratory distress syndrome (ARDS): Patients are not given facemasks but ventilation masks to increase oxygen supply.

The study by Frat et al.[9] compares these ventilation masks to nasal cannula – and they find a significant difference in favor of nasal cannula in 90-day mortality.

The study by Patel et al.[10] compares ventilation masks to an airtight but ventilated helmet around the patient´s head. The trial was stopped early based on predefined criteria for efficacy – the mask group was significantly worse in intubation rate, ventilator-free days and overall mortality. While the authors discuss a slightly higher positive endexpiratory pressure (PEEP) in the ventilation mask group being responsible for this, a meta-analysis by Guo et al.[11] shows that a high PEEP is actually correlated with better outcome.

Therefore, the aim of this study is to prove which one of these concepts / hypotheses can be confirmed by comparing CFR between two groups, one with and one without mask mandates. The state of Kansas, USA has over 2.8 million residents. During summer 2020, Kansas State issued a mask mandate, but it allowed its 105 counties to either opt out or issue their own mask mandate. Out of the 81 counties that had opted out and did not issue their own mask mandate, 8 larger cities had issued a mask mandate.

The comparison of counties within one state has many advantages: Differences in access to and quality of the health system, testing numbers, culture and behavior regarding health and mask usage, climate and different time of infection peaks are all minimal.

In addition, the comparison of infection rates among these counties has already been done by Van Dyke et al[1], so I can herein focus on CFR.

For all of these reasons, I chose Kansas for this study, to answer the most important question: Whether mask mandates actually safe or cost lives during COVID-19 pandemic.

Method

I use a 3+2 -step-model for the analysis of the data.

Step 1: Splitting up the counties in two groups, mask mandated counties (MMC) and counties without mask mandate (noMMC).

Step 2: Parallelizing both groups by excluding counties, trying to exclude as few counties and population as possible to keep the sample as large as possible.

Step 3: Analyzing the data, including the calculation of a risk ratio (RR) for MMC compared to noMMC.

If there is a significant RR, I also use steps 4a and 4b:

Step 4a: Check for infection rate correlated bias (Does a difference in infection rate or a testing bias between groups negate the significant effect on RR?)

Step 4b: Confounder check (Can the difference in RR be explained by something other than SARS-CoV-2?)

Step 1: Splitting up the counties in two groups

Using the information on counties with facemasks from Van Dyke et al.[1], I split the 105 counties into counties with mask mandates (MMC) and counties without mask mandates (noMMC).

Then, I checked noMMC that had known cities with mask mandates for the percentage of the county population that was represented by this/those city/cities (Table 1).

If the city's population was within +/-20% of half of the county's population (that is, between 30% and 70%), the county was excluded. If the city's population represented more than 70% of the county, I moved the county to MMC group. If the city's population represented less than 30% of the county, the counties remained in noMMC group.

Step 2: Parallelizing the groups

I then began excluding counties from both groups to align counties for comparison purposes (parallelization). I chose the crude death rate (CDR) for this purpose as it represents age and pre-existing illness in the underlying population. Both are the most important known factors for death by COVID-19, and they also influence death with a positive test only, so both groups need to have almost the same CDR to be comparable. A comparison of raw CDR showed that it varied from 575.8 to 2010.1 (deaths per 100,000 people per year) between Kansas' counties.

I then modified the CDR of each county for 2019 by subtracting deaths from sources that are clearly not a risk factor for COVID-19 to prevent statistical anomalies when comparing CDR, like an accumulation of deaths from other causes that are related to neither old age nor pre-existing illness. These were pregnancy complications, birth defects, conditions of perinatal period (early infancy), sudden infant death syndrome, motor vehicle accidents, all other accidents and adverse effects, suicide, homicide, and other external causes.

This modified CDR (mCDR) of the counties was then population-weighted (multiplied with population of county divided by population of group) and added up to calculate the mCDR (total number of expected deaths per 100,000 people per year) of MMC and of noMMC.

In order to have almost the same mCDR in both groups, I would go on to exclude counties with the lowest mCDR in the group with lower mCDR and exclude counties with the highest mCDR in the group with higher mCDR until both groups have the same mCDR.

Therefore, I used a lower mCDR boundary for one group and an upper mCDR boundary for the other, trying to reduce this difference while at the same time trying to keep the percentage of Kansas population included as big as possible.

Note: mCDR was only used for parallelization; it was not used in calculations beyond step 2.

Step 3: Analyzing the data

As the mask mandate was issued on July 3rd, I chose August 1st as starting date to allow counties, cities, residents, institutions, shops etc. to adjust to the mask mandate and prevent overlap with time before the mask mandate as the effect of mask mandates cannot be visible immediately.

I chose October 15th as ending point as I had proof of mask mandates up to that point, and there were additional mask mandates made a few weeks after that date.

I used these dates for the number of infected.

The COVID-19 death count in Kansas is not personalized, meaning a counted death is not related to the dead person's infection date. After referring to Khalili et. al.[12], I chose to calculate the deaths 14 days delayed after COVID-19 infection time period. In order to mitigate the influence of start and ending of the time interval, I calculated the number of death as the average of death differences between August 7th and October 22nd, August 14th and October 29th as well as August 21st and November 5th. This way, infections and deaths both span 76 days.

Based on these numbers, I calculated infection rates and CFR for both groups.

I then created a fourfold table with two rows and two columns.

Rows are noMMC and MMC, columns are survivors (number of infected reduced by number of deaths) and dead (number of deaths).

Using that table, I calculated chi² (α=0.05), RR (MMC to noMMC) and 95%CI to determine whether the mask mandates significantly increase or decrease CFR by COVID-19.

Step 4a: Infection rate correlated bias check (optional)

In case that there is a significant RR, I would check whether a difference in infection rate explains the difference in CFR. For this, $\lambda_{\text{low-CFR}}$ would be the infection rate of the group with lower CFR, and $\lambda_{\text{high-CFR}}$ would be the infection rate of group with higher CFR.

There would be two options:

1) The group with low CFR also has a lower infection rate.

If $\lambda_{\text{low-CFR}} < \lambda_{\text{high-CFR}}$, there might be a testing bias

The hypothesis to this would be, that if both groups had been tested equally and both had equal infection rate, the CFR would not be significant. In order to proof this hypothesis, I would reduce the number of deaths in the group with lower CFR by multiplying it with the factor (λ_{low} / λ_{high}), correct the fourfold table from step 3 and repeat the calculation of Chi², RR, and 95%CI.

2) The group with lower CFR has a higher infection rate.

If $\lambda_{low\text{-}CFR} > \lambda_{high\text{-}CFR}$, there might be a bias by protection.

The hypothesis would be, that if those that are protected by a reduced infection rate were factored in, the CFR would not be significant. In order to proof this hypothesis, I increase the amount of infected people in the group with higher CFR by the multiplying it with the factor (λ_{low} / λ_{high}),), correct the fourfold table from step 3 and repeat the calculation of Chi², RR, and 95%CI.

Step 4b: Confounder check (optional)

In case that there is a significant RR, I would check whether a confounder causes the RR (for MMC) to increase or decrease independently from SARS-CoV-2 infection.

The hypothesis would be that there is a confounder in mask-mandated counties that causes increase or decrease the RR independently from SARS-CoV-2.

If this were true, the effect of masks would occur not only in the infected population but also among the not infected population under mask mandate. This can be proven wrong if the potential effect does not align with overall excess mortality in Kansas.

Therefore, either I calculate the additional deaths by mask mandates or the reduced death by mask mandates (for RR and both its 95% CI as by step 3).

These additional/reduced deaths are calculated as the absolute value of

$$(1/\phi - 1) * \text{death}_{MMC}$$

where ϕ is RR (or the value of the 95% CI), and death_{MMC} is the number of deaths in MMC.

I then calculate the expected additional/reduced deaths in all non-infected in all MMC counties by division through the number of infected in MMC (from step 3) and multiplication with total population in all MMC (from step 1).

I then compare the result to the (total) Kansas non-COVID-19 excess mortality during the corresponding weeks as already calculated by CDC. This is done by calculating and adding up the difference between non-COVID-19 deaths and the average expected number of deaths for each given week. The total is the non-COVID-19 excess deaths.

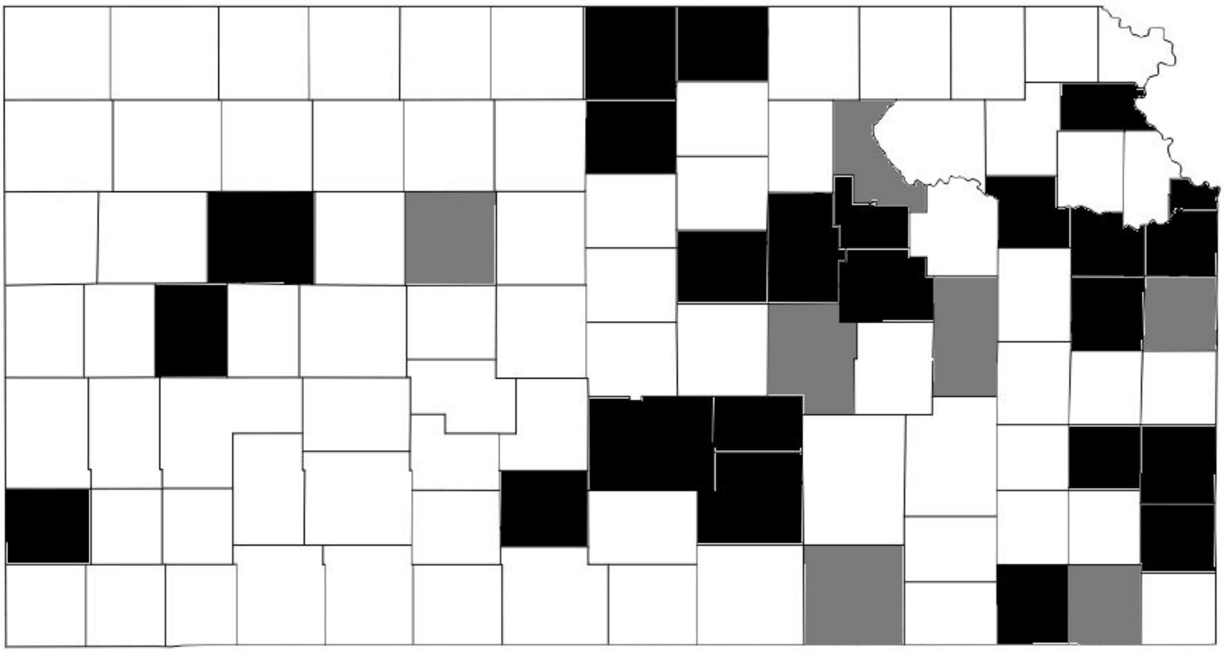
By dividing this number through the expected additional/reduced deaths in all non-infected in all MMC countries, I can estimate the proportion of the RR increase/decrease calculated in step 3 that is *not* related to COVID-19 and thus the influence of possible confounders.

Results

Step 1: Splitting up the counties in two groups

Figure 1 gives an overview of the mask mandates in Kansas counties.

Figure 1 Mask mandates in Kansas counties

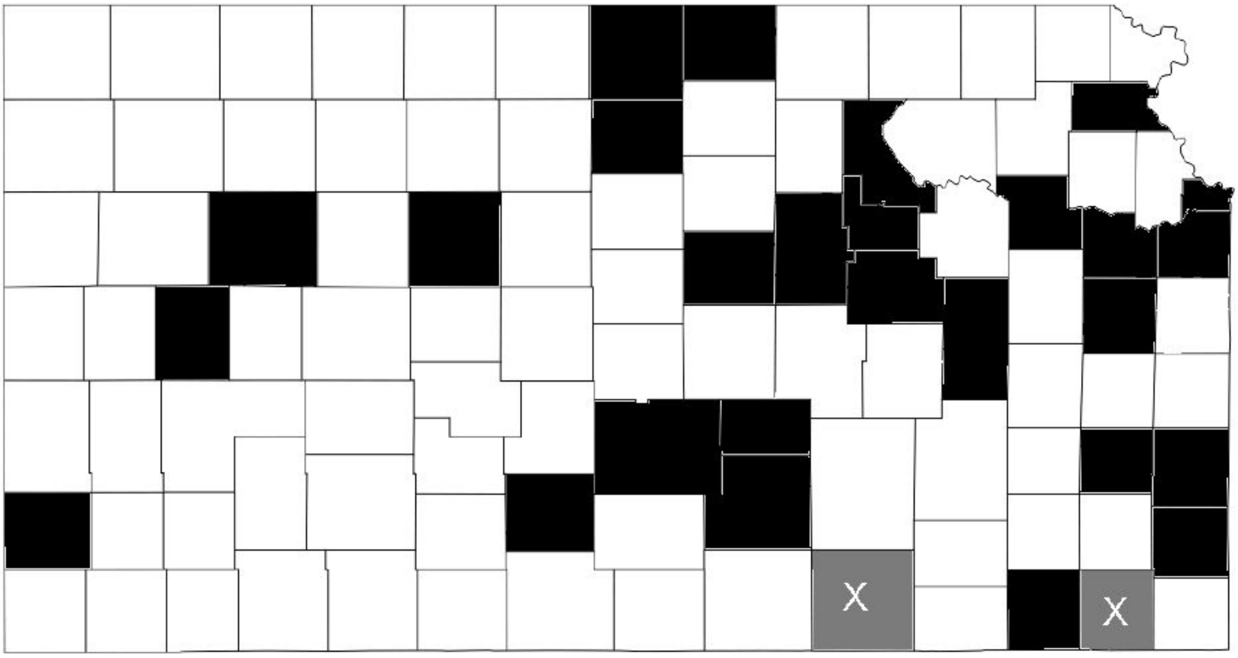


black: county with mask mandate
grey: larger city with mask mandate in county without mask mandate
white: county without mask mandate

Evaluation of the Cities with mask mandates in noMMC is shown in Table S1.

Figure 2 shows the result of these evaluations.

Figure 2 Kansas counties after step 1



black: MMC
white: noMMC
'X': county excluded

Step 2: Parallelizing the groups

For the noMMC, I calculated a mCDR of 1,012.6, while the MMC had a mCDR of 782.5.

Figure S1 (Supplemental appendix) shows the scatterplot of mCDR and CFR by county and after step 1.

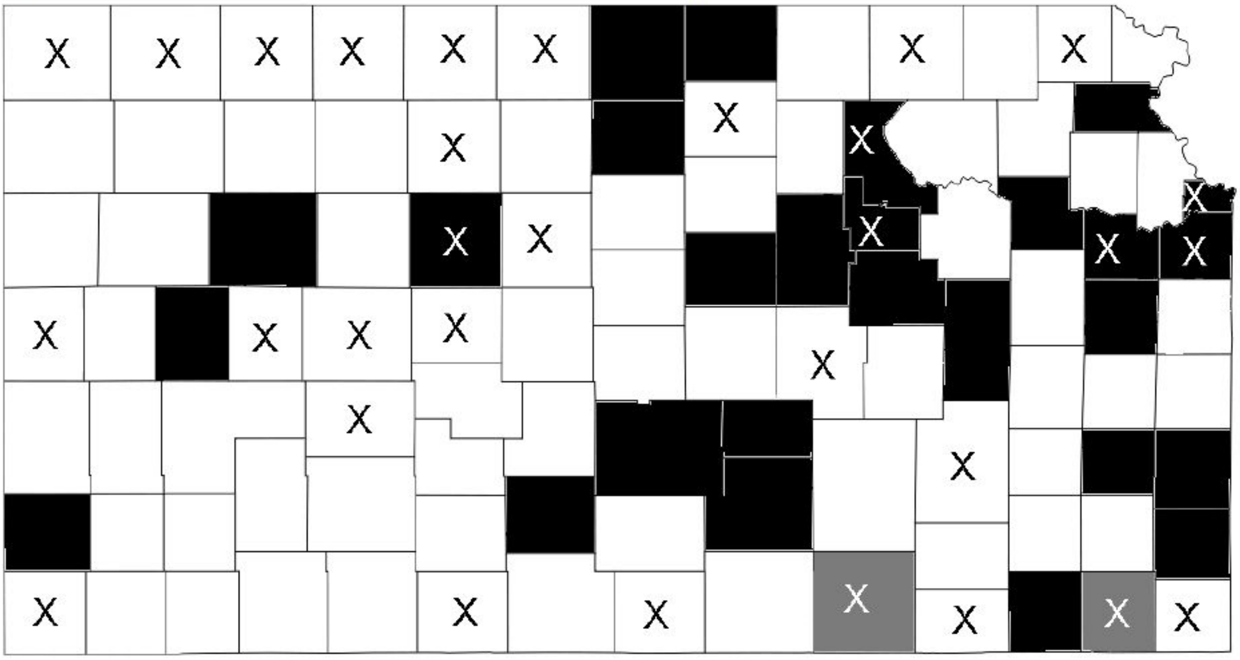
In order to parallelize both groups in terms of mCDR, I excluded counties with the lowest mCDR from MMC and with the highest mCDR from no MMC.

I found that with mCDR boundary of >800 for MMC and <1,350 for noMMC the difference in mCDR between both groups became 0.5 (926.2 vs. 925.7) so I settled for these boundaries.

These boundaries eliminated 31 counties (mostly small counties from noMMC) and 41.3% of the population (mostly from MMC). Note that this narrowly still includes Sedgewick counties 516,042 people (mCDR 802.5).

Figure 3 shows the counties after step 2.

Figure 3 Kansas counties after step 2



black: MMC
white: noMMC
'X': county excluded

The names of these final counties and their corresponding group can be found in table S2 (supplemental appendix).

As a sidenote, it is also possible to find a constellation that excludes Sedgewick county. The boundaries of mCDR >805 for MMC and mCDR >600 for noMMC result in 8.7 difference in mCDR (less than one percent)). Because this constellation almost halves the population of MMC, in order to keep the sample size as big as possible, I did not use these boundaries. However, I still performed the steps 3, 4a and 4b with these boundaries. The results are equally highly significant, don't diverge and can be seen in table S3 (supplementary appendix).

Step 3: Analyzing the data

NoMMC group included 638,955 people, MMC included 1,072,139.

For the noMMC, this left 9,880 infected (infection rate 1.55%) and 95 deaths. For the MMC, this left 13,655 infected (infection rate 1.27%) and 241 deaths.

Therefore, the resulting CFR by COVID-19 is 0.96% for noMMC and 1.76% for MMC.

These numbers result in a highly significant ($p<0.0001$) RR of 1.85 for MMC (95%CI 1.51 – 2.10).

Step 4a: Infection rate correlated bias check

As the there is a significant RR and infection rate in noMMC is higher (option 2), I checked for protection bias.

After correcting as described above, I calculated the fourfold table again but with 16,578 infected instead of 13,655 (which would correspond to a CFR of 241/16,578=1.45% for MMC).

These alternative numbers still result in a highly significant (p=0,0005) RR of 1.52 for MMC (95%CI 1.24 – 1.72).

Step 4b: Confounder check (optional)

The additional deaths among infected in MMC are 111 (95%CI 82 – 126). If they were not related to COVID-19, I would expect 17,031 (95%CI 12,582 – 19,333) additional deaths among non-infected.

The average number of expected all-cause deaths for Kansas total from August 2nd to November 7th is 6867 (98 days compared to the studies 76). There were 7382 deaths without COVID-19, resulting in 515 excess deaths not related to COVID.

This already means that non-COVID factors (i.e. possible counfounders) represent less than 3.0% (95%CI 4.1% – 2.7%) of the RR increase, so I deemed neither factoring in noMMC counties among excess deaths nor adjusting the different timespan mentioned above necessary.

Discussion

The most important finding is that, even when factoring in that less people are dying because infection rates are reduced by masks, the mask mandates still cause 1.52 times the number of deaths or 52% more deaths compared to no mask mandates.

The risk for the individual wearing the mask is even higher, because there is an unknown amount of people in MMC who either do not obey mask mandates or who don't go to public places where mask mandates are in effect.

The mask mandates themselves have increased the case fatality rate by 1.85 or by 85% in counties with mask mandates. Because almost all of these additional deaths can be attributed solely to COVID-19 (see step 4b), this number is most likely still underestimated, how much depends on the percentage of people who tested positive for SARS-CoV-2 but did not die with COVID-19 as the underlying cause of death. The study by Cobos-Siles et al.[13] describes that fifteen percent of patients with COVID-19 infection died from decompensation of other pathologies and the cause of death was unrelated to COVID-19 severe complications.

Correcting for this raises the RR for deaths with COVID-19 as the underlying cause of death to 2.10 as demonstrated in table S4. Further research is needed to quantify the amount of deaths in which COVID-19 was not the underlying cause of death; both in populations with and without mask mandates, to further understand the full extent of this effect.

Hypothesis

The explanation for the increased RR by masks is probably that virions that are breezed or coughed out in droplets are stopped in the facemask tissue, and after quick[14] evaporation of the droplets, pure virions are reinhaled from a very short distance when breathing in. For further reference, I refer to this as the 'foegen effect' as I could not find this effect described earlier.

By the 'foegen effect' the virions are not only spreading to other areas (like the olfactory nerve, causing loss of smell) but also (because of their smaller size) deeper into the respiratory tract[15]. They bypass the bronchia and are inhaled deep into the alveoli, where they cause a pneumonia instead of a bronchitis, which would rather be typical for a virus infection. They also bypass the wall of multilayer squamous epithelium that they cannot pass in vitro[16] and most likely cannot pass in vivo. Therefore, the only probable way for the virions to enter the blood vessels is through the alveoli.

The 'foegen effect' also increases overall viral load, because virions that should have been removed from the respiratory tract are returned. The viral reproduction in vivo, including the reproduction of the returned virions, is exponential compared to the linear[17] droplet reduction caused by the mask. Therefore, the number of exhaled or coughed out virions that pass through the facemask will at some point exceed the number of virions shed without facemasks. In addition, the pure virions in the mask might also be blown outwards when breathing out, resulting in aerosol transmission instead of droplet transmission. The consequences these two effects have on infection rates should be evaluated in further research. They might be linked to a resurgence of rhinoviridae.[18]

The use of "better" masks than just a chirurgical face mask (like FFP2, FFP3) with a higher droplet filtering effect probably cause an even stronger 'foegen effect', as the amount of virions potentially reinhaled increases the same way that outward shedding is reduced.

Another very important point to consider is that the long term effects that have been described in association with COVID-19 may all be a direct cause of the 'foegen effect'. With the virus entering alveoli and blood, and not being restricted to the upper respiratory tract and bronchi (as explained above), it can cause damage by initiating (auto)immune reaction in most organs.

Concerning the proposed consequences of the 'foegen effect' – they question whether the main driver for the global death toll and long-term effects of COVID-19 is the “new” spike protein of SARS-CoV-2 (compared to other coronaviridae) or rather the widespread use of masks as recommended by the WHO.

Since ethical principles prevent clinical studies to prove the 'foegen effect' in vivo, and wearing a mask is unblindable, further proving the 'foegen effect' may be very difficult, especially considering that the helmet trial[10] was stopped because results for the mask group were so much worse. However, a sick person breathing out through a mask (without inhaling) and a puppet ‘inhaling’ through that same mask into a particle collector shortly after might proof the ‘foegen effect’.

Conclusion

I conclude that wearing facemasks imposes a great risk on the individual that is **not** mitigated by a reduction in infection rate. Use of facemasks is therefore not only unfit but also contraindicated as epidemiologic intervention.

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Data Sources

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Declaration of conflicts of interest:

The author and his family live in a country with mask mandates (Germany). As a general practitioner, the author has to wear masks at work. No financial conflicts of interests are declared.