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THE EFFECT OF FACE MASKS ON COVID TRANSMISSION: A META-ANALYSIS

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The Effect of Face Masks on Covid Transmission: A Meta-Analysis

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Abstract:
The effect of face masks on Covid-19 transmission is crucial for the health of populations. The effectiveness of face masks in reducing the transmission of Covid-19 varies across primary evidence. To perform a quantitative meta-analysis, we collected 258 estimates from 44 primary studies together with more than 30 variables reflecting the differences among these studies. We examine publication bias by implementing various statistical tests, revealing mild evidence for the phenomenon. Our contribution to other meta-analyses on this topic involves the use of Bayesian and Frequentist model averaging to identify the drivers behind the heterogeneity of the estimates. The results indicate that temperature, geographical latitude, and panel data structure increase the risk of transmission associated with maskwearing. Furthermore, a positive effect is identified for the healthcare setup. In contrast, wearing masks during aerosol-generating procedures decreases the risk of transmission.

JEL: I1, I11, I19, C68,
Keywords: meta-analysis, Covid-19, face masks, pandemic, transmission, publication bias, Bayesian model averaging

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Data and code are available at https://sites.google.com/view/martinaluskova.

1 Introduction

As Covid-19 disease began to spread rapidly, the lives of populations all around the world were influenced. Various measures were implemented to slow down the spread of the contagious disease. Since Covid-19 is transmitted mainly by the droplets spread by an infected individual, all the interventions were centred around social distancing. Social distancing can take various forms: stay-at-home orders, restrictions on opening hours, indoor and/or outdoor gatherings, travelling restrictions, school closures, and more. Nevertheless, the most popular measure was ordering populations to wear face masks. Knowing the true unbiased effect of face masks on Covid-19 transmission is essential not only for the well-being and health of populations but also for proper policy setting during the pandemic. Apart from the health-related reasons for the evaluation of the mentioned effect, we need to consider the economic consequences of the Covid-19 pandemic. As an outcome of social distancing measures, economic activity experienced a major decline. According to The World Bank, the world's GDP annual growth experienced a drop to -3.1% in 2020. Based on a cost-effectiveness analysis the additional incurred costs associated with mask-wearing amount to almost 1 billion USD with the additional 1,121 prevented Covid-19 cases per million subjects with 328 quality-adjusted life years gained (Bagepally *et al.*, 2021). These results are however sensitive to the effectiveness of face masks in preventing Covid-19. Primary studies report varying estimates both within and between studies, and their results are often inconclusive. Moreover, no meta-analysis uses modern methods for the evaluation of publication bias and addressing model uncertainty. Lastly, the paper's results are of great importance for future pandemics.

The objective of this paper is to assess the literature published on the effect of face masks on Covid transmission and perform a quantitative meta-analysis. To do so, we collected 258 estimates from 44 studies, their standard errors, and the variables representing the differences among the studies. We estimate the true value of the effect corrected for publication bias. Publication bias is a serious issue present in the majority of published literature (Stanley, 2005). Since the publication of a paper is often determined by the statistical significance of its results, the authors engage in the manipulation of sample sizes and specification of models to achieve significance (Gerber *et al.*, 2008; Rothstein *et al.*, 2005; Brodeur *et al.*, 2018). To examine whether publication bias is present in the collected literature on the mentioned effect, we implement several modern statisti-

cal tests such as the FAT-PET with different specifications (OLS, Fixed effects, Between effects), and weights. Secondly, we apply a variety of current techniques such as the Endogenous kink model by Bom & Rachinger (2019), the Stem-based method as suggested by Furukawa (2019), the Selection model as in Andrews & Kasy (2019), and more. Thirdly, methods allowing for endogeneity such as FAT-PET with instrumental variable, p-uniform* method as proposed by van Aert & Van Assen (2019) and Caliper tests (Gerber *et al.*, 2008) are employed. Based on the results of performed tests, we conclude that there is mild evidence for publication bias.

Apart from publication bias detection the majority of enumerated methods can be used to estimate the effect beyond bias. The significant estimates of risk associated with face mask-wearing range from -0.187 to -0.440. These values can be interpreted as follows: Wearing a face mask is associated with a reduced risk of Covid-19 infection by 18.7% to 44%. Such results suggest a significant protective ability against Covid-19. As a consequent implication in the case of another wave of Covid-19 or a variant resistant to available vaccines, we recommend face masks be used. This paper also determines the potential drivers behind the heterogeneity of estimates of the effect of face masks on Covid-19 transmission. It is not unlikely that the estimated effects of primary studies vary not only because of the publication bias but also because of different settings of the studies, methodology and many other factors including the geographical location and the temperature. Despite several meta-analyses already published on the mentioned effect, they all contain several drawbacks. Firstly, the meta-analysis by Chu *et al.* (2020) published in the Lancet evaluates the effect of face masks, however, the studies included in the meta-analysis are focused on various respiratory diseases, not on Covid-19 specifically. The number of included studies on Covid-19 regarding mask use is as low as four. Including other respiratory illnesses in the meta-analysis can be seen in papers by Jefferson *et al.* (2023); Liang *et al.* (2020); Chaabna *et al.* (2021). Moreover, the findings of mentioned meta-analyses are contrasting. While Chu *et al.* (2020) reports immense protective abilities of face masks, Jefferson *et al.* (2023) finds little to no difference in wearing a mask compared to not wearing one. In addition, we contribute to the literature by performing a quantitative meta-analysis of studies on Covid-19 only. Furthermore, we focus on the examination of heterogeneity and determining its drivers as this was not included in greater detail in the mentioned meta-analyses. Since many variables reflecting the differ-

ences among the studies are collected, the model uncertainty needs to be addressed. As a solution, we apply the Bayesian and Frequentist model averaging. We found the temperature, geographical latitude, panel data structure, risk ratio estimate type, healthcare set-up, standard error and age to have a positive effect on the risk of Covid-19 infection associated with mask-wearing. The positive effect means that for these variables masks provide lower protection. On the other hand, performing an aerosol-generating procedure has a negative effect. The interpretation of such a result is that mask-wearing is essential during these procedures. Moreover, as a robustness check, the Bayesian model averaging is estimated with different model priors and g-priors yielding highly comparable posterior inclusion probabilities for the variables.

Lastly, the contribution of this paper lies in the implementation of new meta-analysis approaches developed in economics, and psychology. These methods provide much more credible results compared to the ones used in other meta-analyses. Moreover, we improve other meta-analyses on the topic by including 44 studies specifically on Covid-19. As compared to other authors, a wide spectrum of modern meta-regression methods is used. In addition, we go beyond just estimating the true value of the effect of face masks on Covid transmission and determine the drivers behind the heterogeneity of the estimates.

The paper is structured as follows. Section 2 describes in detail the procedure used to obtain the data, and the recalculation of both effects and standard errors to achieve comparability of the estimates. Section 3 focuses on the examination of publication bias by various modern methods. Section 4 implements the model averaging techniques to explain the drivers of heterogeneity. Section 5 presents the implied estimates and Section 6 summarises the paper.

2 Data

To construct the dataset, we first search the Google Scholar database for relevant studies. Google Scholar is considered superior to other databases because of its ability to search through the full text of studies. In this way, we can include studies that do not have all the desirable keywords combined in the title or abstract (Gechert *et al.*, 2022). Additionally, including only one query for one database allows the search process to be replicated. The details of the literature search and a full list of included studies can be found in

Appendix A. Moreover, for a study to be included in the quantitative meta-analysis, the effect has to be reported as Relative Risk (RR), Odds Ratio (OR), Hazard Ratio (HR), increase in the number of identified Covid-19 cases for both treatment and control groups or relative change in Covid cases. The study has to report standard errors, confidence intervals or p-values, and sample size. In addition, there needs to be exact information on the intervention, and control group and its definition.

The number of studies included in the meta-analysis is 44. Out of these studies, we collect 258 estimates. Apart from the effects and their standard errors, we collect variables on the estimation methods, sample size, the data type used in the primary studies, variables on publication, relevant control variables included in the models, variables on study setting and country-level variables. Together with corresponding variables the dataset consists of more than 9,300 data points.

To perform a meta-analysis one needs the effect from the studies to be directly comparable. All the effects were recalculated to the risk of Covid-19 infection. There are several reasons for this decision. Firstly, the risk of infection is centred around zero. This means that if there would be zero risk of infection, the corresponding estimate would be $= 0$ as well. On the other hand, estimates expressed in OR and RR are centred around one, meaning that if there is no effect found, the corresponding estimate would be $= 1$. As a result, the tests performed on these estimates and the computation of standard errors would not be straightforward and would require additional adjustments. Secondly, RR, OR and relative change in Covid-19 cases can be easily recalculated to the risk of infection. On the other hand, the recalculation of the effect expressed as a relative change in Covid-19 cases to OR would require more complex computations. The third reason for not choosing OR as a common measure of effects, despite being the most represented, is interpretation difficulties. Moreover, Higgins *et al.* (2019) suggest that the OR is the hardest measure in terms of understanding, and application, and is often misinterpreted by researchers. Throughout the data collection, 7 estimate types are identified. The methods for recalculating each type of estimate can be found below.

Risk Ratio For studies, that report their estimates as risk ratio, we can use Equation 1 to express RR as 1 plus risk. Thus, to recalculate RR as the risk of Covid-19 infection,

we subtract 1 from the estimate.

$$RR = \frac{risk_{treated}}{risk_{control}} = \frac{risk_{control} + risk_{change}}{risk_{control}} = 1 + \frac{risk_{change}}{risk_{control}} = 1 + risk \tag{1}$$

$$risk = RR - 1 \tag{2}$$

Apart from the risk ratio, we can find terms relative risk or rate ratio in the literature. The use of these measures is, however, inconsistent. The main difference is that the risk ratio and relative risk compare the incidence of an event between treatment and control groups. Whereas, the rate ratio uses the incidence rate in two time intervals. In the studies included in the meta-analysis, the time intervals are implemented to differentiate the treatment and control period. As a result, we can treat all of the mentioned ratios similarly.

Prevalence Ratio Estimates reported as prevalence ratios can be considered equivalent to the RR. The only recalculation needed is subtracting 1 from the estimate.

Hazard ratio The Hazard ratio is different from RR because it takes into account not only the number of events occurring during the observation period but also the timing. Despite the two ratios not being identical, their interpretation is the same. Spruance *et al.* (2004) suggests that the hazard ratio is an approximation of RR. To standardise the hazard ratio, we subtract 1 from the estimate.

Odds Ratio If authors report their estimates as an odds ratio, we can use the following formula described by Zhang & Yu (1998) to recalculate them to the risk of Covid-19 infection.

$$risk = \frac{OR}{1 - p_0 + p_0 * OR} - 1 \tag{3}$$

Where p_0 represents the Covid-19 incidence of the control group. As already mentioned, the OR tends to be misinterpreted as RR. This practice is however troubling. If $p_o < 10\%$ the odds ratio estimated by logistic regression can approximate the risk ratio. On the other hand, the higher the incidence, the less precise the approximation is (Zhang & Yu, 1998).

Percentage Increase For studies reporting the estimates as a percentage increase, we implement the following standardisation.

$$risk = \frac{percentage\_increase}{100} \tag{4}$$

Change Studies that report their estimates as a change to the absolute number of Covid-19 cases need the following standardisation.

$$risk = \frac{risk_{change}}{risk_{base}} \tag{5}$$

Regression Coefficient Studies that report the estimates of the effect of masks on the log weekly case growth rate were standardised according to the following equation based on the interpretation of results of the study by Karaivanov *et al.* (2021).

$$risk = exp(estimate) - 1 \tag{6}$$

Similar to the estimates, their standard errors need to be recalculated or determined based on p-values or confidence intervals.

Delta Method Firstly, if the standard error is reported, but the estimate needs to be standardised, we employ the Delta Method. We are able to use the Delta Method only for the studies that report their estimates as the change to the absolute number of Covid-19 cases. Thus, the Delta Method has the following form.

$$\begin{aligned} se(risk) = var\left(\frac{risk_{change}}{risk_{base}}\right)^{\frac{1}{2}} = \left(\left(\frac{1}{risk_{base}}\right)^2 var(risk_{change})\right)^{\frac{1}{2}} = \\ = \frac{se(risk_{change})}{risk_{base}} \end{aligned} \tag{7}$$

Calculation using p-value If a study reports p-values only, we determine the corresponding t-statistic and calculate the standard error for a recalculated estimate using the t-statistic.

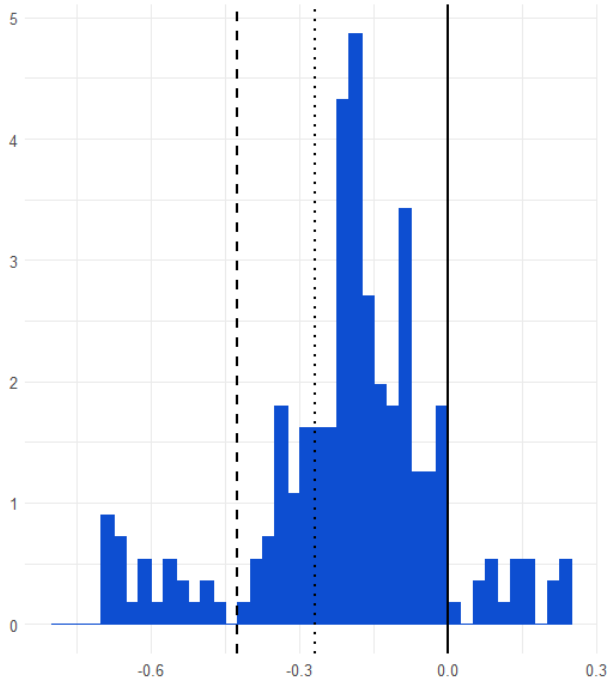
Calculation using confidence intervals For studies reporting confidence intervals, we calculate the standard error according to the following equation for 95% confidence

intervals. The upper and lower bounds of the confidence interval first need to be adjusted based on the method used to recalculate the effect.

$$se(risk) = \frac{(CI_{upper} - CI_{lower})}{3.92} \tag{8}$$

After collecting the data, we carefully inspect the dataset and pay specific attention to the outliers. We excluded two observations from the analysis, the number of studies was thus reduced to 43. Next, we winsorize the effects and their standard errors at 1% level. Figure 1 shows the distribution by effect magnitude. The estimates of the effect

Figure 1: Effect distribution



Note: The figure shows the distribution by effect magnitude using winsorized data. The outliers are excluded from the figure but are included in the calculation. The solid vertical line represents 0 intercept. The dotted vertical line is a simple mean and the dashed vertical line represents the weighted mean.

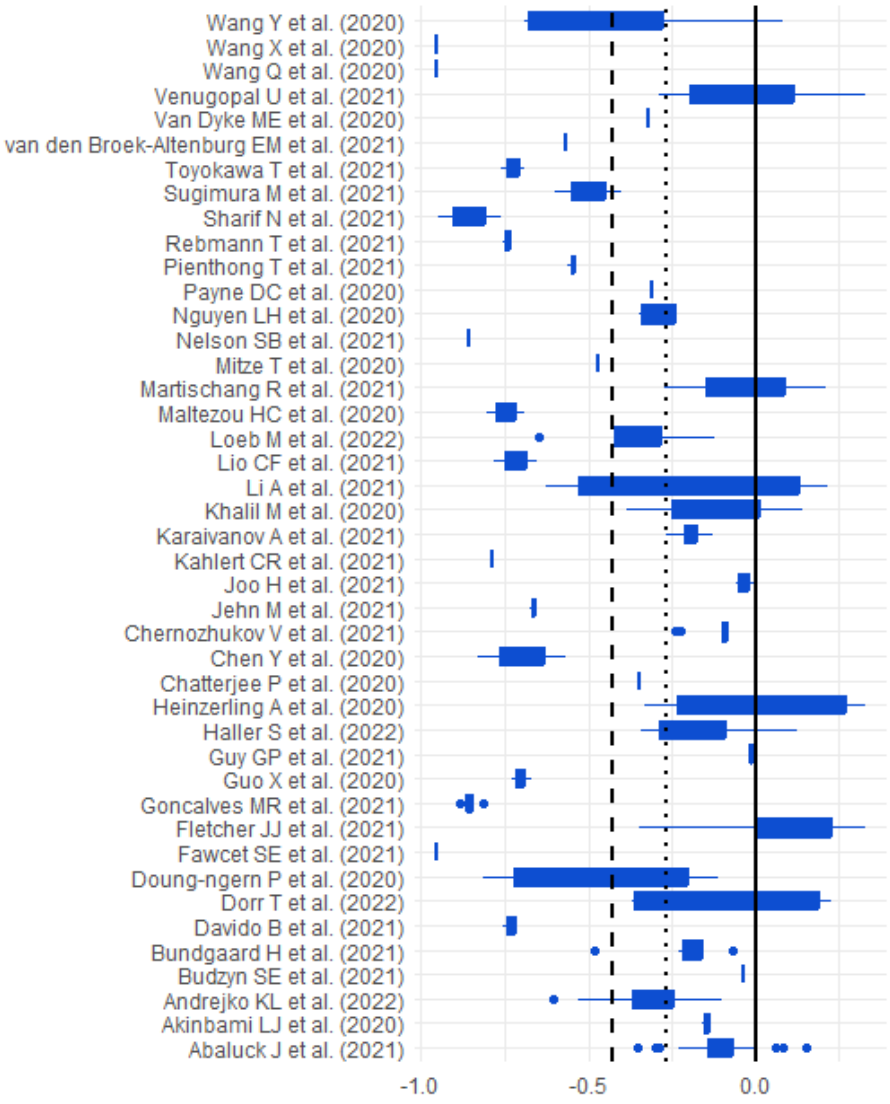
of face masks on Covid-19 transmission range from -0.956 to 0.33 with a mean value of -0.268, and median value of -0.2. Additionally, we calculate the mean weighted by the inverse number of observations per study which equals -0.425. The simple mean is

higher because studies presenting a higher number of estimates of higher values drive the mean closer to zero. Additionally, the mean value is higher than the median which would suggest a skewed dataset. Chu *et al.* (2020) report the effect as $RR = 0.34$ which can be expressed as $risk = 0.66$. This estimate is much higher than the mean and median values for our collected effects. If we take into account, that even though Chu *et al.* (2020) included 44 studies in their meta-analysis, only 4 of them were focused on face masks and Covid-19, their estimates might not be accurate. It is important to mention, that these are just initial remarks based on Figure 1 observation and we cannot draw any conclusions yet. Figure 2 or forest plot displays the estimates across studies. It is apparent from the figure, that estimates vary not only across studies but also within individual studies. Moreover, over 90% of the estimates are negative.

Table 1 shows the mean effect of face masks on Covid-19 transmission for selected subsamples. Some studies or some estimates of studies have their control group protected by lower levels of face masks (respirators for the treatment group and surgical masks for the control group). For these estimates, the mean suggests that wearing a mask might reduce the risk of infection by a lower amount compared to the estimates, where the control group is not protected at all. That would be reasonable since masks might reduce the risk of transmission in the control group as well. For respirators, we can observe a lower conditional mean risk of infection compared to the surgical masks. For panel data, we can see a higher mean likewise. This could be caused by controlling for other social distancing policies. Additionally the policy control variable and panel data variable are highly correlated.

Interestingly, for estimates with an average minimum temperature during the study period higher or equal to 15°C (warm areas) the mean effect of masks on Covid-19 transmission is higher compared to the mean of estimates where the average maximum temperature is lower or equal to 15°C (cold areas). For the estimates computing their effect from data only we calculate their simple and weighted mean in order to check whether the effect was not overestimated (masks would be too effective) in these cases. Both means were closer to zero than the means for the rest of the sample. Additionally, these studies are included in the meta-analysis by Chu *et al.* (2020). The estimates also include results from studies with double zero events, which are highly suggested to be included in a meta-analysis Xiao *et al.* (2021). What is more, they represent only around 5% of all

Figure 2: Risk of Covid-19 infection across included studies



Note: The figure shows the effect box plot for every included study calculated using winsorized data. The solid vertical line represents 0 intercept. The dotted vertical line is a simple mean and the dashed vertical line represents the weighted mean. Each row represents the individual study included in the meta-analysis. For each study, we present the box plot. Where boxes represent the inter-quartile range (from 25% to 75%). The dots are outliers.

Table 1: Conditional means

	Mean	95% CI	n
Full sample	-0.268	(-0.805, 0.269)	256
Methodology and effect type			
RR	-0.165	(-0.681, 0.351)	56
OR	-0.425	(-1.062, 0.211)	96
change	-0.158	(-0.320, 0.003)	82
effect from data	-0.160	(-0.938, 0.618)	15
regression	-0.266	(-0.767, 0.235)	238
logit	-0.426	(-1.058, 0.207)	93
cox	-0.240	(-0.524, 0.043)	25
Study set-up			
personal controls	-0.286	(-0.844, 0.273)	104
policy controls	-0.191	(-0.481, 0.098)	94
healthcare	-0.306	(-0.966, 0.354)	68
AGP	-0.379	(-1.044, 0.287)	34
vaccination available	-0.384	(-0.910, 0.143)	31
Mask variables			
mask frequency = all	-0.312	(-0.864, 0.239)	68
mask frequency = some	-0.126	(-0.468, 0.216)	41
respirator	-0.294	(-0.909, 0.321)	46
surgical mask	-0.213	(-0.698, 0.272)	32
control masked = 1	-0.174	(-0.601, 0.253)	35
control masked = 0	-0.283	(-0.830, 0.265)	221
Data characteristics			
panel data	-0.160	(-0.411, 0.091)	164
individual level	-0.315	(-0.932, 0.301)	172
random trial	-0.148	(-0.428, 0.131)	42
data year = 2020	-0.276	(-0.830, 0.279)	189
data year = 2021	-0.245	(-0.730, 0.240)	67
Country characteristics			
China	-0.637	(-1.164, -0.110)	15
Bangladesh	-0.151	(-0.562, 0.261)	36
Switzerland	-0.175	(-0.549, 0.199)	39
USA	-0.186	(-0.735, 0.363)	68
temperature min $\geq$ 15°C	-0.276	(-0.786, 0.234)	108
temperature max $\leq$ 15°C	-0.491	(-0.989, 0.007)	16

Note: The table displays conditional means of the effect of face masks on Covid-19 transmission and corresponding confidence intervals (CI) for selected sub-samples, n = sub-sample size, RR = relative risk, OR = odds ratio, AGP = aerosol generating procedure.

observations, thus we decided to include them in the dataset.

Lastly, with available vaccination, the mean is lower. Which is likely caused by the majority of studies not controlling for vaccination. Thus the seemingly more protective effect of face masks might be probably caused by omitting the vaccination variables from models of primary studies. These are again only observations based on simple descriptive statistics, which cannot be used to draw any conclusions.

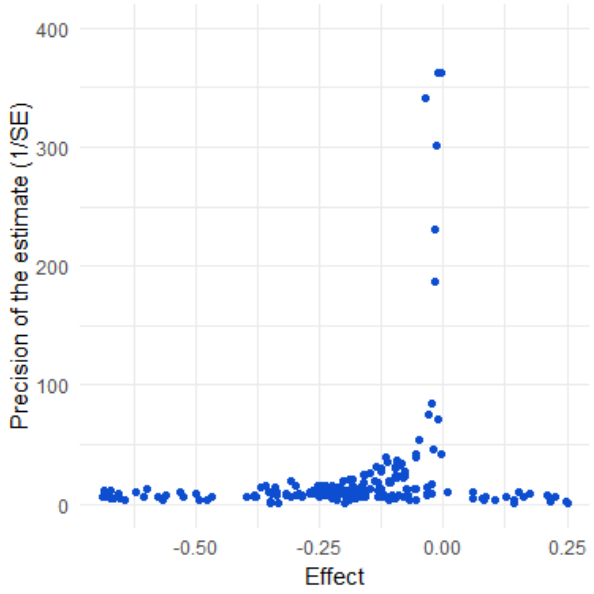
3 Publication Bias

Publication bias is a phenomenon occurring with a preference of researchers for significant effects causing the published papers not to be representative of all the conducted research (Rothstein *et al.*, 2005; Stanley, 2005). The probability of a paper being published is often determined by the significance of its results (Gerber *et al.*, 2008). To achieve the desired significance, researchers indulge in intentionally adjusting the datasets, creating sub-samples, modifying specifications, and p-hacking (Brodeur *et al.*, 2018, 2016).

With the use of meta-regression analysis, publication bias and p-hacking are discovered in the literature on different spheres, among others in economics, social sciences, and medical research (Stanley, 2005). Taking into account that publication bias in medical and related research might have serious consequences for the health of individuals. Some studies, especially at the beginning of the Covid-19 pandemic report a huge protective ability of face masks (Doung-Ngern *et al.*, 2020; Chen *et al.*, 2020; Maltezou *et al.*, 2020; Wang *et al.*, 2020a,b). Combined with uncertainty about the reproduction number of the different variants of Covid-19, populations relying too much on the protective abilities of face masks might have fatal consequences. After examination of the other meta-analyses on the topic, we conclude that the majority of them rely on graphical methods only. Thus, the evaluation of publication bias would benefit from more rigorous methods. The methods that are used in this paper take inspiration from the ones used by Gechert *et al.* (2022); Havranek *et al.* (2021) in their meta-analyses.

The first method we employ is the graphical method for publication bias detection called Funnel plot as in Egger *et al.* (1997). The horizontal axis plots the estimates of the risk of Covid-19 infection associated with mask-wearing versus their accuracy (the inverse of standard errors) on the vertical axis. The estimates with higher precision should be

Figure 3: Funnel plot



Note: The figure shows the funnel plot as presented by Egger *et al.* (1997). Outliers were excluded from the figure.

located around the true value of the risk. On the other hand, the lower the precision of the estimates, the wider the distribution. In our case, it is obvious from Figure 3, that the less precise estimates are located close to the horizontal axis. The funnel plot's ability to graphically detect publication bias lies in the following: If the publication bias is not present in the sample, the funnel should appear symmetrical. In the presence of publication bias, the funnel plot will lose its symmetry, introducing skewness and asymmetry.

One can notice the estimates with the highest precision are centred around a negative value relatively close to zero. On the right side of the plot, there are missing values, compared to the left side of the funnel, which only has estimates with low precision. Such a pattern could suggest possible publication bias. The interesting fact, that we consider important to mention, is that the mean and weighted mean values of the effect are both negative and noticeably different from zero, which is caused by a large number of studies with negative effects of higher magnitude. Generally, the true effect being negative would be in line with the existing theory about mask usage (Ueki *et al.*, 2020; Wilson *et al.*, 2021), and why populations were advised for their use in the first place.

Next, we apply the numerical methods to test for the funnel asymmetry more rigor-

ously. If the publication bias is not present in the collected estimates, the risk of Covid-19 infection associated with mask-wearing should not be correlated with the standard errors of the risk estimates. The relationship could be induced by studies with less precise estimates adjusting their specifications and/or sample sizes to achieve significant results (Stanley, 2005).

As presented in Table 2, Panel A we used five different methods. The estimates from the simple OLS are presented in the first column of the table. The estimated publication bias seems to be quite small and significant only at 10%. The fixed effects (FE) model, accounting for the different characteristics on the study level, is the only model showing a highly significant presence of publication bias. The other three methods do not yield a significant estimate of publication bias. The between effects (BE) model accounts for between-study variance. The last two columns of the table present models weighted by the inverse number of estimates reported per study and the inverse of the variance as in Ioannidis *et al.* (2017). On the other hand, the estimates of the effect beyond bias are all negative and highly statistically significant in four out of five presented models.

Table 2, Panel B shows the methods allowing for a non-linear relationship between effects and standard errors. We implement six methods for estimating the effect beyond bias, and two of these methods to estimate the publication bias. Firstly, we estimate the endogenous kink model as proposed by Bom & Rachinger (2019). The authors developed a meta-regression technique for publication bias correction that locates a kink in the distribution of standard errors. The non-linear method features a horizontal part and a sloped line that together creates the kink. The kink in the standard errors' distribution is chosen so that publication bias is not probable beneath the distinguishing value. The publication bias estimate is again not significant. Next, we estimate a Hierarchical Bayes model according to Allenby & Rossi (2006). With the use of Bayesian statistics, the model utilises the variability of estimates within individual studies and based on these differences determines the weights assigned to each estimate. Similar to the previous method, the publication bias estimate is not significant. Regarding the effect beyond bias, the estimate yields a magnitude similar to the weighted mean of the effects.

The weighted average of adequately powered estimates (WAAP) method includes only the adequately statistically powered observations and runs a weighted meta-regression only on this sub-sample (Ioannidis *et al.*, 2017). As a result, only 75 observations remained

Table 2: A mild evidence for publication bias, corrected effect around -0.2

Panel A: Linear methods					
	OLS	**FE**	**BE**	**Study**	**Precision**
Publication bias	0.074*	-0.436***	-0.306	0.040	-0.436
(Standard error)	(0.038)	(0.068)	(0.222)	(0.038)	(2.104)
Effect beyond bias	-0.282***	-0.187***	-0.243***	-0.197***	-0.187
(Constant)	(0.018)	(0.001)	(0.027)	(0.008)	(0.158)
Observations	256	256	256	256	256
Panel B: Nonlinear methods					
	Stem	**WAAP**	**Top10**	**AK**	**Kink**	**Bayes**
Publication bias					-0.436	0.180
(Standard error)					(1.315)	(0.304)
Effect beyond bias	-0.092	-0.223***	-0.094*	-0.240***	-0.187***	-0.440***
(Constant)	(0.110)	(0.030)	(0.035)	(0.032)	(0.024)	(0.097)
Observations	256	256	256	256	256	256
Panel C: Endogeneity-robust methods						
					IV	**p-uniform***
Publication bias					0.249	0.148***
(Standard error)					(0.191)	(0.068)
Effect beyond bias					-0.221***	-0.422***
(Constant)					(0.028)	(0.111)
Observations					256	256

Note: Panel A: The estimates of regression $risk_{ij} = \beta_0 + \beta_1 * (SE_{risk})_{ij} + u_{ij}$, where $risk_{ij}$ is the i-th estimate of risk from the j-th study. $(SE_{risk})_{ij}$ is the standard error of the i-th estimate of risk from the j-th study. OLS = Ordinary Least Squares, FE = Fixed Effects, BE = Between Effects, Study = estimates weighted by the inverse number of observations reported per study, Precision = estimates weighted by the inverse of standard errors. Panel B: Stem = stem-based method as in Furukawa (2019), WAAP = weighted average of adequately powered estimates (Ioannidis *et al.*, 2017), Top10 = method due to Stanley *et al.* (2010), AK = Selection model due to Andrews & Kasy (2019), Kink = endogenous kink model (Bom & Rachinger, 2019), Bayes = hierarchical Bayes model as in Allenby & Rossi (2006). Panel C: IV = regression taking the inverse of the square root of the number of observations as an instrument for the standard error as in Gechert *et al.* (2022), p-uniform* = method developed by van Aert & Van Assen (2019) is estimated using the method of moments. Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

in the sample. The effect beyond bias coefficient is significant and similar to the estimates from the linear methods. The Stem-based method focuses only on the most precise estimates, the stem of the funnel (Furukawa, 2019). The idea is that the bias would

decrease as the variance increases (given the higher number of observations).

Next, we employ the TOP10 method as discussed by Stanley *et al.* (2010). The author suggests that using only the best 10% of the data can improve the statistical estimation and reduce the publication selection bias, however contradictory to the statistical theory this might be. Nevertheless, the reason for this is that 90% of the data are not representative because of the publication bias. Hence, the remaining 10% of the data should be a better base for efficiently estimating the true effect. The estimated effect beyond bias is significant only at the 10% level and slightly lower than the estimates produced by the other methods. The trustworthiness of the estimate should be in question because of the low number of observations. The last method for non-linear approaches is the Selection model due to (Andrews & Kasy, 2019). The non-parametrically determined probability of a study being published is a function of its results. This probability can be applied in the correction of publication bias.

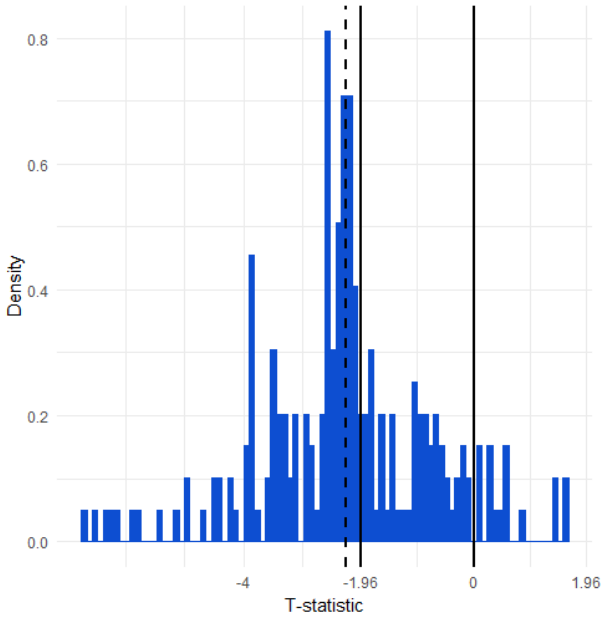
Until now, the methods we discuss assume that the standard errors are exogenous. The issue with this assumption is the following. The standard errors and the effects could be correlated not only because of the presence of publication bias but also as a result of unobserved heterogeneity or measurement errors. We suggest this would be the case for the effects and the standard errors in the collected dataset. As a result of the different methodological approaches used in the primary studies, we expect that some of the methods yield systematically higher standard errors.

Table 2, Panel C shows the results of two methods: IV estimation using the inverse of the square root of the number of observations in primary studies as an instrument for standard errors as suggested by (Gechert *et al.*, 2022). The second method, p-uniform* due to van Aert & Van Assen (2019), identifies a significant presence of publication bias. The effect beyond bias is closer to the weighted mean of the studies compared to the other methods. The idea behind the method is the following. The p-values should be distributed uniformly. However, the publication bias is affecting their distribution. Under publication bias, the significant estimates just below the threshold are over-represented, on the other hand, the estimates with p-values just above the 5% level are under-represented. The goal of the p-uniform* method is to find a value around which the p-values follow a uniform distribution.

Let us present the last method allowing for endogeneity in standard errors. Caliper

test as described by Gerber *et al.* (2008). Authors suggest that publication bias is the cause of possible jumps in the distribution of t-statistics at significant thresholds of 1.96 and -1.96. Additionally, it is possible to evaluate the behaviour at the 0 threshold. Figure 4 shows the distribution of t-statistics for collected effects of face masks on Covid-19 transmission. Looking at the -1.96 threshold we can see a jump in the distribution, with more observations just above the threshold. At 1.96 we cannot observe any t-statistics. Since the majority of our effects are negative, so are the corresponding t-statistics, resulting in no values at this threshold. At 0 we do not observe any major jumps in the distribution. However, only a simple glance at the figure suggests that there are more effects in the $(-1.96, 0)$ interval than in the $(0, 1.96)$ one.

Figure 4: t-statistics distribution



Note: The figure shows the distribution of t-statistics. The solid vertical lines display -1.96 and 0 thresholds. The dashed vertical line represents the simple mean of t-statistics. The outliers are excluded from the figure but remain in the calculations.

The Caliper test as compared to the previous methods does not assume any relationship between effects and standard errors. The idea is to compare the number of t-statistics above and below the significance threshold to detect whether publication bias is present. Table 3 shows the performed Caliper tests for -1.96 and 0 thresholds for presented Caliper widths. We would like to note that as a result of the sample size the Caliper widths are

set quite wide to have enough observations in the given Calipers. Since the Caliper of the width 0.2 contains only 9 t-statistics we would rather not interpret the results of the test. For Caliper widths 0.5, 0.6, 0.7 and 0.8 significant results are obtained. The value 0.684 for 0.5 Caliper width can be interpreted as follows. For interval (-2.21, -1,71) there are 38 t-statistics and 68.4% of them are below the -1.96 threshold. The percentage is even higher for wider Calipers. For the 0 threshold, we do not detect any significant results.

Table 3: Publication bias: Caliper tests

	Threshold = -1.96	n	**Threshold = 0**	n
Caliper width = 0.2	0.778*	9		
	(0.147)			
Caliper width = 0.3	0.632	19		
	(0.114)			
Caliper width = 0.4	0.583	24		
	(0.103)			
Caliper width = 0.5	0.684**	38		
	(0.076)			
Caliper width = 0.6	0.745***	51	0.615	13
	(0.062)		(0.140)	
Caliper width = 0.7	0.724***	58	0.556	18
	(0.059)		(0.121)	
Caliper width = 0.8	0.730***	63	0.579	19
	(0.056)		(0.116)	

Note: The table displays the results of the Caliper test as described by Gerber *et al.* (2008) for presented Caliper widths. Caliper width of 0.1 does not contain enough observations even for the -1.96 threshold, standard errors are presented in parentheses. The value 0.684 for 0.5 Caliper width can be interpreted as follows. For interval (-2.21, -1,71) there are 38 t-statistics and 68.4% of them are below the -1.96 threshold, *p<0.1; **p<0.05; ***p<0.01.

To summarise, we find significant evidence for publication bias only in some of the performed tests. For tests that identify a significant presence of publication bias in the literature, its magnitude was considered mild. According to Doucouliagos & Stanley (2013) the estimate of $|\hat{\beta}_1| < 1$ is considered to be mild evidence of publication bias. These findings are in line with the ones by Chu *et al.* (2020). The effect beyond bias is estimated to be negative and statistically significant for almost all of the methods. In addition, we do not detect any positive significant estimates of the effect beyond bias. As a result, we believe that the true effect is negative, but its magnitude is varying. The significant estimates of risk associated with face mask-wearing range from -0.187 to

-0.440. These values can be interpreted as follows: Wearing a face mask is associated with a reduced risk of Covid-19 infection by 18.7% to 44%.

4 Heterogeneity

The varying effect is likely driven by different factors. To provide the reader with a better understanding of how the studies differ, we explain the rationale behind the collected variables. The variables together with their definitions can be seen in Table 4. Firstly, to account for the possibility of different methods producing systematically higher or lower estimates, we collect the corresponding dummy variables. The majority of estimates are obtained by the implementation of a certain type of regression (Logistic, Cox and corresponding HR, weighted OLS,...). These estimates account for almost 95% of all collected effects. We define dummy variables for the type of estimated effect: RR, OR, absolute and relative change in Covid-19 cases. The last variable is joined with a dummy variable for percentage increase, and a dummy for regression coefficient. The reason for joining the three variables is the similarity in the approach of the primary studies which estimated the types of effects.

Secondly, we consider it beneficial to include a set of dummy variables to code the control variables included in the models. Unfortunately, the vast majority of primary studies included in the meta-analysis as well as other studies that we encountered during the identification procedure are of low transparency. The studies do not include the full list of variables included in their models. However, we collect at least two dummy variables: controlling for personal and policy characteristics. Brooks-Pollock *et al.* (2021) suggest that these variables influence the transmission of Covid-19, and their omission would result in biased estimates. Moreover, controlling for vaccination in the models of primary studies is almost non-existent. The first reason could be that the studies were conducted before the vaccination was publicly available. However, even the studies carried out during the periods when vaccination was already available failed to control for the vaccination. To account for vaccination, a dummy variable indicating its availability in a given region and time period is coded. Next, we distinguish between studies performed in healthcare and non-healthcare environments. In addition, for healthcare studies, we code a variable representing whether healthcare workers performed aerosol generating procedures (AGP).

Performing AGP increases the risk of infection due to the transmission route of Covid-19 (Lotfi *et al.*, 2020; Liu *et al.*, 2020). We also code a dummy variable for studies that use a lower grade of protection as their control. Such a practice would likely produce different estimates compared to having non-masked individuals as controls. Studies designed as randomised clinical trials are properly randomised and the control and treatment groups should be comparable in terms of the characteristics of included subjects (National Cancer Institute, 2022). Consequently, estimates from these studies should be close to the true effect.

Thirdly, we code a dummy variable for a panel data structure. Following the reporting guidelines by Havranek *et al.* (2020), we collect the variables for the sample size, and the average year in which the study is performed. Regarding the publication characteristics, we collect a dummy for studies published in a peer-reviewed journal, and a variable reflecting the impact factor of a journal in which a study is published. Unfortunately, we are not able to use the RePEc factor, since the majority of journals are not of an economic nature. As a substitute, we use the JCR database which also includes medical journals. Next, we collect a variable on the year of the publication, and the number of citations in Google Scholar in line with Havranek *et al.* (2020).

According to World Health Organisation (2022), the number of Covid-19 cases varies for different countries. We include country variables geographical latitude of the region where the study is conducted, and the minimum and maximum average temperatures. The temperature variables are determined based on the area and time period of the study. As suggested by Shi *et al.* (2020) and Notari (2021) temperature is a fundamental factor in the dynamics of Covid-19 transmission. In addition, we include a variable representing the average age of the subjects.

Now that we have characterised potential drivers behind the heterogeneity of the effects, we follow with the estimation. To avoid multicollinearity, we need to exclude some of the correlated variables. We do so based on their variance inflation factors (VIF), and correlation coefficients (correlation table is presented in Appendix B). As a result, 8 variables are removed and 18 are selected for the analysis (all of them with VIF score below 7). If we were to estimate models with all of the possible combinations of variables, the number of these models would be 2^{18}. To address the model uncertainty and over-specification with likely biased and imprecise results, we use the approach commonly used

Table 4: Description of variables

Variable	Description	Mean	SD
effect	the risk of Covid-19 infection	-0.268	0.274
standard error	standard error of the risk of Covid-19 infection	0.187	0.470
Methodology and effect type			
RR	=1 if a study reports the estimates as relative risk	0.219	0.414
OR	=1 if a study reports the estimates as odds ratio	0.375	0.485
change	=1 if a study reports the estimates as a change to identified Covid-19 cases	0.320	0.468
effect from data	=1 if the effect is calculated from data	0.059	0.235
regression	=1 if the effect is estimated using any kind of regression	0.930	0.256
logit	=1 if the effect is estimated using regression with logit link	0.363	0.482
cox	=1 if the effect is estimated using Cox regression	0.098	0.297
Study set-up			
personal controls	=1 if a study controlled for personal characteristics in its model	0.406	0.492
policy controls	=1 if a study controlled for other social distancing policies in its model	0.367	0.483
healthcare	=1 if a study was conducted in a healthcare setting	0.266	0.443
AGP	=1 if subjects were performing AGP	0.133	0.340
vaccination available	=1 if vaccination was available during the period and country in which a study was performed	0.121	0.327
random trial	=1 if a study is of random trial design	0.164	0.371
individual level	=1 if a study was performed on an individual level	0.672	0.470
control masked	=1 if the control group was using a lower grade of mask	0.137	0.344
Data characteristics			
panel data	=1 if the data is of panel structure	0.641	0.481
sample size	logarithm of a sample size of a study	7.904	2.060
year data	the year in which a study was performed (average for more years)	2020.262	0.440
Country and individual characteristics			
min temperature	average minimum temperature for a study's time period and area	3.555	10.559
max temperature	average maximum temperature for a study's time period and area	27.012	5.772
latitude	logarithm of latitude of study's area	3.627	0.429
age	logarithm of the average age of study's subjects	3.684	0.211
Publication characteristics			
peer review	=1 if published in peer-reviewed journal	0.992	0.088
impact	logarithm of the impact factor of a journal	2.348	1.588
year publication	logarithm of the year in which a study was published	2021.039	0.619
citations	logarithm of the number of citations on Google Scholar	4.262	1.395

Note: The table displays the definition, mean, and standard deviation of variables eligible for use in meta-regressions, AGP = Aerosol Generating Procedure, personal characteristics = age, education, number of children, household members, occupation, *et cetera*, policy controls = stay-at-home orders, restrictions on public gatherings, school closures, *et cetera*, year and temperature variables are not in log scales because of low variability and negative values respectively.

in meta-analyses, Bayesian model averaging (BMA) (Havranek *et al.*, 2018; Havranek & Sokolova, 2020; Havranek *et al.*, 2021; Gechert *et al.*, 2022).

BMA selects the most appropriate subset of regressors based on the models' performance. Each regressor is then assigned a posterior inclusion probability (PIP) that is calculated based on the performances of the models, where the given regressor is included (Eicher *et al.*, 2011; Steel, 2020). We use a Markov chain Monte Carlo (Madigan *et al.*, 1995) algorithm to select for estimation only those models from the model space where performance is high. We set the g-prior for each coefficient to the common practice in meta-analyses, a unit information prior, meaning the weights are set to give the prior the same importance as one individual observation (Eicher *et al.*, 2011; Havranek *et al.*, 2018). In addition, we need to choose the prior for the model probability. As a baseline, we select the dilution prior, which is more suitable when dealing with potential collinearity. For small sample sizes - as is the case of this paper, the models are prone to suffer from collinearity. The dilution prior tackles the issue by giving less weight to the models suffering from a lot of collinearity (George *et al.*, 2010). Figure 5 shows the graphical results of BMA. In addition, we implement the frequentist model averaging (FMA). Following the practice of Gechert *et al.* (2022) we employ Mallow's criteria as weights (Hansen, 2007), and orthogonalization of the covariate space as in Amini & Parmeter (2012). The results of both BMA and FMA are presented in Table 5.

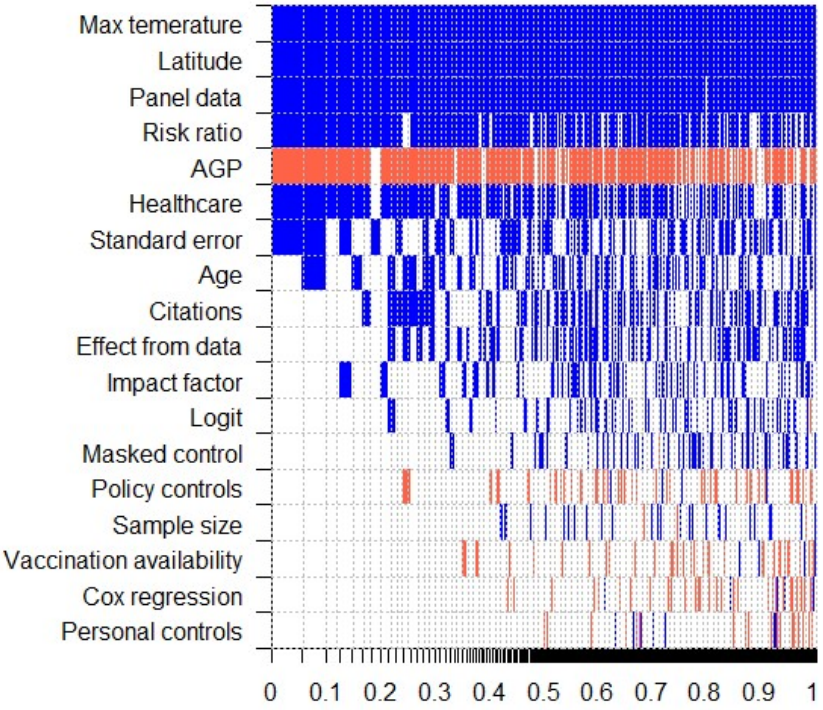
The highest posterior probability inclusion can be seen for variables representing the maximum average temperature and geographical latitude. The coefficient for max temperature is positive, which can be interpreted as follows. With increasing maximum temperature the protection provided by masks is lower. This is probably caused by the lower transmission of Covid-19 during summer periods (Shi *et al.*, 2020). For latitude, the interpretation is the following: with increasing latitude, the masks are less effective. This would be caused by lower temperatures for regions with higher latitudes. For variable panel data, we get a positive estimate as well. The reason is that the panel data variable is correlated with the random trial variable which is not included in the model. The reasoning is that these estimates are higher because the panel structure of the data would likely decrease the probability of estimating the effect at a non-representative point in time. As expected, the healthcare variable has also a positive effect. This means that the masks are less protective in the healthcare environment where healthcare professionals

Table 5: The results of BMA and FMA

Response variable: estimate of risk	**Bayesian model averaging** (baseline)			**Frequentist model averaging** (frequentist check)		
	post. mean	post. SD	PIP	coef.	SE	p-value
standard error	0.043	0.051	0.492	0.039	0.042	0.355
intercept	-2.797	NA	1.000	-3.466	0.444	0.000
Methodology and effect type						
RR	0.119	0.065	0.850	0.115	0.066	0.082
effect from data	0.069	0.106	0.365	0.150	0.093	0.106
logit	0.012	0.033	0.164	0.074	0.061	0.228
cox	-0.003	0.019	0.080	-0.004	0.053	0.942
Study set-up						
personal controls	-0.000	0.008	0.058	-0.014	0.031	0.648
policy controls	-0.008	0.029	0.136	-0.032	0.051	0.531
healthcare	0.110	0.076	0.747	0.127	0.060	0.034
AGP	-0.152	0.087	0.832	-0.170	0.056	0.002
vaccination available	-0.005	0.024	0.099	-0.026	0.052	0.620
control masked	0.012	0.037	0.149	0.026	0.060	0.660
Data characteristics						
panel data	0.196	0.047	0.997	0.209	0.053	0.000
sample size	0.001	0.006	0.109	0.006	0.011	0.564
Country and individual characteristics						
max temperature	0.372	0.079	1.000	0.431	0.074	0.000
latitude	0.236	0.049	1.000	0.265	0.050	0.000
age	0.058	0.079	0.419	0.126	0.067	0.060
Publication characteristics						
impact	0.004	0.009	0.229	0.008	0.011	0.446
citations	0.011	0.016	0.410	0.024	0.014	0.073

Note: The table displays the results of Bayesian model averaging with dilution model prior and Frequentist model averaging results, PIP = Posterior Inclusion probability, RR = relative risk, AGP = Aerosol Generating Procedure, max temperature does not contain any negative values, hence it is in log scale, PIP $\in [0.5, 0.75)$ = week evidence, PIP $\in [0.75, 0.9)$ = positive effect, PIP $\in [0.9, 0.99)$ = strong effect, PIP $\in [0.99, 1)$ = decisive effect, the posterior inclusion probability can be considered analogous to the statistical significance of a variable (Kass & Raftery, 1995).

Figure 5: BMA with a dilution model prior and unit information g-prior



Note: The figure shows the Bayesian Model Averaging with the dilution model prior and unit information g-prior. The response variable is the risk of Covid-19 infection. The horizontal axis represents the cumulative posterior model probability (PIP). The regressors are ordered in descending order based on their PIP. The included regressors with positive signs are displayed in blue (dark in grayscale) colour, and with negative signs in red (light in grayscale) colour. The Regressors not included in the model are left without any colour.

are in frequent contact with infected individuals. Lastly, the AGP variable has a negative effect. According to the present author, it can be interpreted as follows: using a face mask during procedures that generate aerosols is essential for decreasing the risk of infection. The risk estimated in the form of RR seems to be systematically higher (lower protection of masks). As apparent from the Table 5 the results of both averaging methods are comparable. In addition to the already presented models, we perform BMA with different g-priors and model priors yielding comparable results.

5 The implied estimate

As a bottom line of the meta-analysis, we present the implied estimates. We derive the estimates of the prominent studies on the effect of face masks on Covid-19 transmission

corrected for publication bias and misspecifications. Firstly, we choose the study by Karaivanov *et al.* (2021). The study is published in the Journal of Health Economics with over 130 citations in Google Scholar. The econometric models estimated in the study are described in great detail with all included control variables. Compared to other studies, the paper stands out for its transparency. The implied estimate equals to -0.136. For the set-up of the study, masks reduce the risk of Covid-19 infection by 13.6%.

Table 6: Implied estimates

Study	Implied estimate	95%CI
Karaivanov *et al.* (2021)	-0.136	(-0.161, -0.111)
Bundgaard *et al.* (2021)	-0.129	(-0.229, -0.030)
Nguyen *et al.* (2020)	-0.157	(-0.288, -0.025)

Secondly, the implied estimate is derived for the study by Bundgaard *et al.* (2021). The reason for choosing the study is its random trial design with proper randomisation of the control and treatment groups. The study is published in the Annals of Internal Medicine with over 350 citations in Google Scholar. The derived estimate equals -0.129. This means, that the masks reduce the risk of infection by 12.9%. The third derived estimate is for a study in a healthcare setting by Nguyen *et al.* (2020). It is published in The Lancet Public Health journal and has over 2,000 citations in Google Scholar. Its implied estimate equals -0.157. In the given context, masks reduce the risk of infection by 15.7%. All of the implied estimates derived for the studies are negative, including the upper bounds of their 95% confidence intervals (Table 6).

6 Conclusion

One might think that the effect of face masks on Covid-19 transmission is strictly a medical topic. However, we would like to emphasise its economic consequences. The Covid-19 pandemic and related social distancing measures caused a sharp decline in the GDP of major economies (Jena *et al.*, 2021). Bagepally *et al.* (2021) suggest that the costs associated with surgical mask-wearing amount to almost one billion USD. Resulting in avoiding more than 1,100 per million cases of Covid-19. However, these costs depend

on the value of the true unbiased effect. In addition, our results could be important for policymakers.

We perform a meta-analysis on the effect of face masks on Covid transmission. We collect 258 estimates of the effect from 44 studies together with corresponding variables on the methodology and effect type, study set-up, data, country and individual, and publication characteristics. Together more than 9,300 data points are collected. Firstly, we examine the publication bias by employing many modern tests. The performed methods are divided into three categories. The linear methods for publication bias detection include a graphical method: funnel plot (Egger *et al.*, 1997), and numerical FAT-PET with different weights. We perform non-linear tests such as endogenous kink model (Bom & Rachinger, 2019), stem-based method (Furukawa, 2019), selection model (Andrews & Kasy, 2019) and more. The last category includes the methods allowing for endogeneity: FAT-PET with instrumental variable, p-uniform* method, and Caliper test. As a result, only some of the tests yield significant estimates of publication bias. Nevertheless, these significant estimates imply only mild evidence of publication bias. Such a result is in line with Chu *et al.* (2020). Apart from the detection of publication bias, these methods estimate the effect beyond bias. The estimate is statistically significant for almost all of the methods ranging from -0.187 to -0.440 which can be interpreted as face masks being effective in reducing the risk of Covid-19 infection by 18.7% to 44%. In contrast, Chu *et al.* (2020) finds the immense protective effect of face masks. On the other hand, Jefferson *et al.* (2023) estimates the protective effect of masks to be small to none.

In the second part of the paper, we focus on model averaging to examine the heterogeneity. We perform Bayesian and Frequentist model averaging with different priors. The purpose of implementing the averaging method is to identify the important variables influencing the effect of face masks on Covid-19 transmission. 18 out of 26 eligible variables were used for the averaging. We find the following variables to have a positive effect on the risk of transmission associated with mask-wearing (decreasing the effectiveness of masks): the temperature, geographical latitude, panel data structure, risk ratio estimate type, healthcare set-up, standard error and age. Performing aerosol-generating procedures has a negative effect on risk (increasing the effectiveness of masks). Unfortunately, we cannot compare these results to the results of other authors, since they use different designs for their meta-analyses and do not evaluate the heterogeneity and its drivers in greater detail.

Nevertheless, the results are in line with what we expect to find. In addition, performed robustness checks yield very similar outcomes. As a bottom line of this meta-analysis, we derive the implied estimates representing the effect of prominent studies after correcting for publication bias and misspecifications. The implied estimates range from -0.129 to -0.157. This means that the masks reduce the risk of transmission by 12.9% to 15.7% for the set-ups of these studies.

Lastly, we present some drawbacks. Despite including 44 primary studies in the meta-analysis, we can collect only above 250 estimates. In addition, we are not able to collect specific controls included in the models of primary studies. This issue is caused by the low transparency of medical studies. We at least collect dummy variables for policy and personal characteristics controls. Nevertheless, the two dummy variables are not statistically significant.

References

Abaluck, J., L. H. Kwong, A. Styczynski, A. Haque, M. A. Kabir, E. Bates-Jefferys, E. Crawford, J. Benjamin-Chung, S. Raihan, S. Rahman, S. Benhachmi, N. Z. Bintee, P. J. Winch, M. Hossain, H. M. Reza, A. A. Jaber, S. G. Momen, A. Rahman, F. L. Banti, T. S. Huq, S. P. Luby, & A. M. Mobarak (2022): "Impact of community masking on Covid-19: A cluster-randomized trial in Bangladesh." *Science* **375(6577)**: p. eabi9069.

van Aert, R. C. & M. Van Assen (2019): "Correcting for publication bias in a meta-analysis with the p-uniform* method." MetaArXiv preprint.

Akinbami, L. J., N. Vuong, L. R. Petersen, S. Sami, A. Patel, S. L. Lukacs, L. Mackey, L. A. Grohskopf, A. Shehu, & J. Atas (2020): "SARS-CoV-2 seroprevalence among healthcare, first response, and public safety personnel, Detroit metropolitan area, Michigan, USA, May–June 2020." *Emerging infectious diseases* **26(12)**: p. 2863.

Allenby, G. M. & P. E. Rossi (2006): "Hierarchical bayes models." *The handbook of marketing research: Uses, misuses, and future advances* pp. 418–440.

Amini, S. M. & C. F. Parmeter (2012): "Comparison of model averaging techniques: Assessing growth determinants." *Journal of Applied Econometrics* **27(5)**: pp. 870–876.

Andrejko, K. L., J. M. Pry, J. F. Myers, N. Fukui, J. L. DeGuzman, J. Openshaw, J. P. Watt, J. A. Lewnard, S. Jain, C. COVID *et al.* (2022): "Effectiveness of face mask or respirator use in indoor public settings for prevention of SARS-CoV-2 infection, California, February–December 2021." *Morbidity and Mortality Weekly Report* **71(6)**: p. 212.

Andrews, I. & M. Kasy (2019): "Identification of and correction for publication bias." *American Economic Review* **109(8)**: pp. 2766–94.

Bagepally, B. S., M. Haridoss, M. Natarajan, K. Jeyashree, & M. Ponnaiah (2021): "Cost-effectiveness of surgical mask, N-95 respirator, hand-hygiene and surgical mask with hand hygiene in the prevention of Covid-19: Cost effectiveness analysis from Indian context." *Clinical Epidemiology and Global Health* **10**: p. 100702.

Bom, P. R. & H. Rachinger (2019): "A kinked meta-regression model for publication bias correction." *Research synthesis methods* **10(4)**: pp. 497–514.

Brodeur, A., N. Cook, & A. Heyes (2018): "Methods matter: P-hacking and causal inference in economics and finance." *IZA DP* **(11796)**.

Brodeur, A., M. Lé, M. Sangnier, & Y. Zylberberg (2016): "Star wars: The empirics strike back." *American Economic Journal: Applied Economics* **8(1)**: pp. 1–32.

van den Broek-Altenburg, E. M., A. J. Atherly, S. A. Diehl, K. M. Gleason, V. C. Hart, C. D. MacLean, D. A. Barkhuff, M. A. Levine, & J. K. Carney (2021): "Jobs, housing, and mask wearing: Cross-sectional study of risk factors for Covid-19." *JMIR Public Health and Surveillance* **7(1)**: p. e24320.

Brooks-Pollock, E., J. M. Read, A. R. McLean, M. J. Keeling, & L. Danon (2021): "Mapping social distancing measures to the reproduction number for Covid-19." *Philosophical Transactions of the Royal Society B* **376(1829)**: p. 20200276.

Budzyn, S. E., M. J. Panaggio, S. E. Parks, M. Papazian, J. Magid, M. Eng, & L. C. Barrios (2021): "Pediatric Covid-19 cases in counties with and without school mask requirements, United States, July 1–September 4, 2021." *Morbidity and Mortality Weekly Report* **70(39)**: p. 1377.

Bundgaard, H., J. S. Bundgaard, D. E. T. Raaschou-Pedersen, C. von Buchwald, T. Todsen, J. B. Norsk, M. M. Pries-Heje, C. R. Vissing, P. B. Nielsen, U. C. Winsløw *et al.* (2021): "Effectiveness of adding a mask recommendation to other public health measures to prevent SARS-CoV-2 infection in Danish mask wearers: A randomized controlled trial." *Annals of internal medicine* **174(3)**: pp. 335–343.

Chaabna, K., S. Doraiswamy, R. Mamtani, & S. Cheema (2021): "Facemask use in community settings to prevent respiratory infection transmission: A rapid review and meta-analysis." *International Journal of Infectious Diseases* **104**: pp. 198–206.

Chatterjee, P., T. Anand, K. J. Singh, R. Rasaily, R. Singh, S. Das, H. Singh, I. Praharaj, R. R. Gangakhedkar, B. Bhargava *et al.* (2020): "Healthcare workers & SARS-CoV-2 infection in India: A case-control investigation in the time of Covid-19." *The Indian journal of medical research* **151(5)**: p. 459.

Chen, Y., X. Tong, J. Wang, W. Huang, S. Yin, R. Huang, H. Yang, Y. Chen, A. Huang, Y. Liu *et al.* (2020): "High SARS-CoV-2 antibody prevalence among healthcare workers exposed to Covid-19 patients." *Journal of Infection* **81(3)**: pp. 420–426.

Chernozhukov, V., H. Kasahara, & P. Schrimpf (2021): "Causal impact of masks, policies, behavior on early Covid-19 pandemic in the US." *Journal of econometrics* **220(1)**: pp. 23–62.

Chu, D. K., E. A. Akl, S. Duda, K. Solo, S. Yaacoub, H. J. Schünemann, A. El-Harakeh, A. Bognanni, T. Lotfi, M. Loeb *et al.* (2020): "Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and Covid-19: A systematic review and meta-analysis." *The lancet* **395(10242)**: pp. 1973–1987.

Davido, B., S. Gautier, I. Riom, S. Landowski, C. Lawrence, A. Thiebaut, S. Bessis, V. Perronne, H. Mascitti, L. Noussair *et al.* (2021): "The first wave of Covid-19 in hospital staff members of a tertiary care hospital in the greater Paris area: A surveillance and risk factors study." *International Journal of Infectious Diseases* **105**: pp. 172–179.

Dörr, T., S. Haller, M. F. Müller, A. Friedl, D. Vuichard, C. R. Kahlert, & P. Kohler (2022): "Risk of SARS-CoV-2 acquisition in health care workers according to cumulative patient exposure and preferred mask type." *JAMA Network Open* **5(8)**: p. e2226816.

Doucouliagos, C. & T. D. Stanley (2013): "Are all economic facts greatly exaggerated? Theory competition and selectivity." *Journal of Economic Surveys* **27(2)**: pp. 316–339.

Doung-Ngern, P., R. Suphanchaimat, A. Panjangampatthana, C. Janekrongtham, D. Ruampoom, N. Daochaeng, N. Eungkanit, N. Pisitpayat, N. Srisong, O. Yasopa *et al.* (2020): "Case-control study of use of personal protective measures and risk for SARS-CoV-2 infection, Thailand." *Emerging infectious diseases* **26(11)**: p. 2607.

Egger, M., G. D. Smith, M. Schneider, & C. Minder (1997): "Bias in meta-analysis detected by a simple, graphical test." *Bmj* **315(7109)**: pp. 629–634.

Eicher, T. S., C. Papageorgiou, & A. E. Raftery (2011): "Default priors and predictive performance in Bayesian model averaging, with application to growth determinants." *Journal of Applied Econometrics* **26(1)**: pp. 30–55.

Fawcett, S. E., M. S. Madhusudhan, E. N. Gaddam, M. J. Almario, S. R. Masih, D. D. Klute-Evans, J. C. Johnson, C. D. Stroud, J. A. Dolan-Caren, M. A. Ben-Aderet, & et al. (2023): "Transmission risk of severe acute respiratory coronavirus virus 2 (SARS-CoV-2) to healthcare personnel following unanticipated exposure to aerosol-generating procedures: Experience from epidemiologic investigations at an academic medical center." *Infection Control & Hospital Epidemiology* **44(2)**: p. 325–327.

Fletcher, J. J., E. C. Feucht, P. Y. Hahn, T. N. McGoff, D. J. Dehart, M. E. El Mortada, & R. G. Grifka (2022): "Healthcare-acquired coronavirus disease 2019 (COVID-19) is less symptomatic than community-acquired disease among healthcare workers." *Infection Control & Hospital Epidemiology* **43(4)**: pp. 490–496.

Furukawa, C. (2019): "Publication bias under aggregation frictions: Theory, evidence, and a new correction method." Available at SSRN: `https://ssrn.com/abstract=3362053`.

Gechert, S., T. Havranek, Z. Irsova, & D. Kolcunova (2022): "Measuring capital-labor substitution: The importance of method choices and publication bias." *Review of Economic Dynamics* **45**: pp. 55–82.

George, E. I. *et al.* (2010): "Dilution priors: Compensating for model space redundancy." *Borrowing Strength: Theory Powering Applications–A Festschrift for Lawrence D. Brown* **6**: pp. 158–165.

Gerber, A., N. Malhotra *et al.* (2008): "Do statistical reporting standards affect what is published? Publication bias in two leading political science journals." *Quarterly Journal of Political Science* **3(3)**: pp. 313–326.

Gonçalves, M. R., R. C. P. Dos Reis, R. P. Tólio, L. C. Pellanda, M. I. Schmidt, N. Katz, S. S. Mengue, P. C. Hallal, B. L. Horta, M. F. Silveira *et al.* (2021): "Social distancing, mask use, and transmission of severe acute respiratory syndrome coronavirus 2, Brazil, April–June 2020." *Emerging infectious diseases* **27(8)**: p. 2135.

Guo, X., J. Wang, D. Hu, L. Wu, L. Gu, Y. Wang, J. Zhao, L. Zeng, J. Zhang, & Y. Wu (2020): "Survey of Covid-19 disease among orthopaedic surgeons in Wuhan, People's Republic of China." *The Journal of bone and joint surgery. American volume* **102(10)**: pp. 847–854.

Guy Jr, G. P., F. C. Lee, G. Sunshine, R. McCord, M. Howard-Williams, L. Kompaniyets, C. Dunphy, M. Gakh, R. Weber, E. Sauber-Schatz *et al.* (2021): "Association of state-issued mask mandates and allowing on-premises restaurant dining with county-level Covid-19 case and death growth rates, United States, March 1–December 31, 2020." *Morbidity and Mortality Weekly Report* **70(10)**: p. 350.

Haller, S., S. Güsewell, T. Egger, G. Scanferla, R. Thoma, O. B. Leal-Neto, D. Flury, A. Brucher, E. Lemmenmeier, J. C. Möller *et al.* (2022): "Impact of respirator versus surgical masks on SARS-CoV-2 acquisition in healthcare workers: A prospective multicentre cohort." *Antimicrobial Resistance & Infection Control* **11(1)**: pp. 1–11.

Hansen, B. E. (2007): "Least squares model averaging." *Econometrica* **75(4)**: pp. 1175–1189.

Havranek, T., Z. Irsova, L. Laslopova, & O. Zeynalova (2021): "Skilled and unskilled labor are less substitutable than commonly thought." Available at SSRN: `https://ssrn.com/abstract=3783950`.

Havranek, T., Z. Irsova, & O. Zeynalova (2018): "Tuition fees and university enrolment: A meta-regression analysis." *Oxford Bulletin of Economics and Statistics* **80(6)**: pp. 1145–1184.

Havranek, T. & A. Sokolova (2020): "Do consumers really follow a rule of thumb? Three thousand estimates from 144 studies say "probably not"." *Review of Economic Dynamics* **35**: pp. 97–122.

Havranek, T., T. D. Stanley, H. Doucouliagos, P. Bom, J. Geyer-Klingeberg, I. Iwasaki, W. R. Reed, K. Rost, & R. C. van Aert (2020): "Reporting guidelines for meta-analysis in economics." *Journal of Economic Surveys* **34(3)**: pp. 469–475.

Heinzerling, A., M. J. Stuckey, T. Scheuer, K. Xu, K. M. Perkins, H. Resseger, S. Magill, J. R. Verani, S. Jain, M. Acosta *et al.* (2020): "Transmission of Covid-19 to health care personnel during exposures to a hospitalized patient, Solano County, California, February 2020." *Morbidity and Mortality Weekly Report* **69(15)**: p. 472.

Higgins, J. P. T., J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (2019): *Cochrane handbook for systematic reviews of interventions*. John Wiley & Sons. Google-Books-ID: cTqyDwAAQBAJ.

Ioannidis, J. P. A., T. D. Stanley, & H. Doucouliagos (2017): "The Power of Bias in Economics Research." *The Economic Journal* **127(605)**: pp. F236–F265.

Jefferson, T., L. Dooley, E. Ferroni, L. A. Al-Ansary, M. L. van Driel, G. A. Bawazeer, M. A. Jones, T. C. Hoffmann, J. Clark, E. M. Beller *et al.* (2023): "Physical interventions to interrupt or reduce the spread of respiratory viruses." `https://doi.org/10.1002/14651858.CD006207.pub6`.

Jehn, M., J. Mac McCullough, A. P. Dale, M. Gue, B. Eller, T. Cullen, & S. E. Scott (2021): "Association between K–12 school mask policies and school-associated Covid-19 outbreaks, Maricopa and Pima Counties, Arizona, July–August 2021." *Morbidity and Mortality Weekly Report* **70(39)**: p. 1372.

Jena, P. R., R. Majhi, R. Kalli, S. Managi, & B. Majhi (2021): "Impact of Covid-19 on GDP of major economies: Application of the artificial neural network forecaster." *Economic Analysis and Policy* **69**: pp. 324–339.

Joo, H., G. F. Miller, G. Sunshine, M. Gakh, J. Pike, F. P. Havers, L. Kim, R. Weber, S. Dugmeoglu, C. Watson *et al.* (2021): "Decline in Covid-19 hospitalization growth rates associated with statewide mask mandates—10 states, March–October 2020." *Morbidity and Mortality Weekly Report* **70(6)**: p. 212.

Kahlert, C. R., R. Persi, S. Güsewell, T. Egger, O. B. Leal-Neto, J. Sumer, D. Flury, A. Brucher, E. Lemmenmeier, J. C. Möller *et al.* (2021): "Non-occupational and occupational factors associated with specific SARS-CoV-2 antibodies among hospital workers–a multicentre cross-sectional study." *Clinical Microbiology and Infection* **27(9)**: pp. 1336–1344.

Karaivanov, A., S. E. Lu, H. Shigeoka, C. Chen, & S. Pamplona (2021): "Face masks, public policies and slowing the spread of Covid-19: Evidence from Canada." *Journal of Health Economics* **78**: p. 102475.

Kass, R. E. & A. E. Raftery (1995): "Bayes factors." *Journal of the american statistical association* **90(430)**: pp. 773–795.

Khalil, M., M. M. Alam, M. K. Arefin, M. R. Chowdhury, M. R. Huq, J. A. Chowdhury, A. M. Khan *et al.* (2020): "Role of personal protective measures in prevention of Covid-19 spread among physicians in Bangladesh: A multicenter cross-sectional comparative study." *SN comprehensive clinical medicine* **2(10)**: pp. 1733–1739.

Li, A., J. Slezak, A. M. Maldonado, J. Concepcion, C. V. Maier, & G. Rieg (2021): "SARS-CoV-2 positivity and mask utilization among health care workers." *JAMA Network Open* **4(6)**: p. e2114325.

Liang, M., L. Gao, C. Cheng, Q. Zhou, J. P. Uy, K. Heiner, & C. Sun (2020): "Efficacy of face mask in preventing respiratory virus transmission: A systematic review and meta-analysis." *Travel Medicine and Infectious Disease* **36**: p. 101751.

Lio, C. F., H. H. Cheong, C. I. Lei, I. L. Lo, L. Yao, C. Lam, & I. H. Leong (2021): "Effectiveness of personal protective health behaviour against Covid-19." *BMC Public Health* **21(1)**: p. 827.

Liu, Y., Z. Ning, Y. Chen, M. Guo, Y. Liu, N. K. Gali, L. Sun, Y. Duan, J. Cai, D. Westerdahl *et al.* (2020): "Aerodynamic analysis of SARS-CoV-2 in two Wuhan hospitals." *Nature* **582(7813)**: pp. 557–560.

Loeb, M., A. Bartholomew, M. Hashmi, W. Tarhuni, M. Hassany, I. Youngster, R. Somayaji, O. Larios, J. Kim, B. Missaghi *et al.* (2022): "Medical masks versus N95 respirators for preventing Covid-19 among health care workers: A randomized trial." *Annals of Internal Medicine* **175(12)**: pp. 1629–1638.

Lotfi, M., M. R. Hamblin, & N. Rezaei (2020): "Covid-19: Transmission, prevention, and potential therapeutic opportunities." *Clinica Chimica Acta* **508**: pp. 254–266.

Madigan, D., J. York, & D. Allard (1995): "Bayesian graphical models for discrete data." *International Statistical Review/Revue Internationale de Statistique* pp. 215–232.

Maltezou, H. C., X. Dedoukou, M. Tseroni, P. Tsonou, V. Raftopoulos, K. Papadima, E. Mouratidou, S. Poufta, G. Panagiotakopoulos, D. Hatzigeorgiou *et al.* (2020): "SARS-CoV-2 infection in healthcare personnel with high-risk occupational exposure: Evaluation of 7-day exclusion from work policy." *Clinical Infectious Diseases* **71(12)**: pp. 3182–3187.

Martischang, R., A. Iten, I. Arm, M. Abbas, B. Meyer, S. Yerly, I. Eckerle, J. Pralong, J. Sauser, J.-C. Suard *et al.* (2022): "Severe acute respiratory coronavirus virus 2 (SARS-CoV-2) seroconversion and occupational exposure of employees at a Swiss university hospital: A large longitudinal cohort study." *Infection Control & Hospital Epidemiology* **43(3)**: pp. 326–333.

Mitze, T., R. Kosfeld, J. Rode, & K. Wälde (2020): "Face masks considerably reduce Covid-19 cases in Germany." *Proceedings of the National Academy of Sciences* **117(51)**: pp. 32293–32301.

National Cancer Institute (2022): "National cancer institute dictionary of cancer terms." `https://www.cancer.gov/publications/dictionaries/cancer-terms/def/randomized-clinical-trial`, Last accessed on 2022-12-29.

Nelson, S. B., C. M. Dugdale, A. Bilinski, D. Cosar, N. R. Pollock, & A. Ciaranello (2021): "Prevalence and risk factors for in-school transmission of SARS-CoV-2 in Massachusetts K-12 public schools, 2020-2021." `https://doi.org/10.1101/2021.09.22.21263900`.

Nguyen, L. H., D. A. Drew, M. S. Graham, A. D. Joshi, C.-G. Guo, W. Ma, R. S. Mehta, E. T. Warner, D. R. Sikavi, C.-H. Lo, S. Kwon, M. Song, L. A. Mucci, M. J. Stampfer, W. C. Willett, A. H. Eliassen, J. E. Hart, J. E. Chavarro, J. W. Rich-Edwards, R. Davies, J. Capdevila, K. A. Lee, M. N. Lochlainn, T. Varsavsky, C. H. Sudre, M. J. Cardoso, J. Wolf, T. D. Spector, S. Ourselin, C. J. Steves, A. T. Chan, C. M. Albert, G. Andreotti, B. Bala, B. A. Balasubramanian, L. E. Beane-Freeman, J. S. Brownstein, F. J. Bruinsma, J. Coresh, R. Costa, A. N. Cowan, A. Deka, S. L. Deming-Halverson, M. Elena Martinez, M. E. Ernst, J. C. Figueiredo, P. Fortuna, P. W. Franks, L. B. Freeman, C. D. Gardner, I. M. Ghobrial, C. A. Haiman, J. E. Hall, J. H. Kang, B. Kirpach, K. C. Koenen, L. D. Kubzansky, J. V. Lacey, Jr, L. Le Marchand, X. Lin, P. Lutsey, C. R. Marinac, M. E. Martinez, R. L. Milne, A. M. Murray, D. Nash, J. R. Palmer, A. V. Patel, E. Pierce, M. M. Robertson, L. Rosenberg, D. P. Sandler, S. H. Schurman, K. Sewalk, S. V. Sharma, C. J. Sidey-Gibbons, L. Slevin, J. W. Smoller, C. J. Steves, M. I. Tiirikainen, S. T. Weiss, L. R. Wilkens, & F. Zhang (2020): "Risk of Covid-19 among front-line health-care workers and the general community: A prospective cohort study." *The Lancet Public Health* **5(9)**: pp. e475–e483.

Notari, A. (2021): "Temperature dependence of Covid-19 transmission." *Science of The Total Environment* **763**: p. 144390.

Page, M. J., J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan *et al.* (2021): "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews." *International journal of surgery* **88**: p. 105906.

Payne, D. C., S. E. Smith-Jeffcoat, G. Nowak, U. Chukwuma, J. R. Geibe, R. J. Hawkins, J. A. Johnson, N. J. Thornburg, J. Schiffer, Z. Weiner *et al.* (2020): "SARS-CoV-2 infections and serologic responses from a sample of US Navy service members—USS Theodore Roosevelt, April 2020." *Morbidity and Mortality Weekly Report* **69(23)**: p. 714.

Piapan, L., P. De Michieli, F. Ronchese, F. Rui, M. Mauro, M. Peresson, L. Segat, P. D'Agaro, C. Negro, M. Bovenzi *et al.* (2020): "Covid-19 outbreak in healthcare workers in hospitals in Trieste, North-east Italy." *Journal of Hospital Infection* **106(3)**: pp. 626–628.

Pienthong, T., T. Khawcharoenporn, P. Apisarnthanarak, D. J. Weber, & A. Apisarnthanarak (2022): "Factors associated with coronavirus disease 2019 (Covid-19) among Thai healthcare personnel with high-risk exposures: The important roles of double masking and physical distancing while eating." *Infection Control & Hospital Epidemiology* **43(12)**: pp. 1978–1980.

Rebmann, T., T. M. Loux, L. D. Arnold, R. Charney, D. Horton, & A. Gomel (2021): "SARS-CoV-2 Transmission to masked and unmasked close contacts of university students with Covid-19, St. Louis, Missouri, January–May 2021." *Morbidity and Mortality Weekly Report* **70(36)**: p. 1245.

Rothstein, H. R., A. J. Sutton, & M. Borenstein (2005): *Publication bias in meta-analysis: Prevention, assessment and adjustments*. John Wiley & Sons.

Sharif, N., K. J. Alzahrani, S. N. Ahmed, R. R. Opu, N. Ahmed, A. Talukder, R. Nunia, M. S. Chowdhury, I. J. Nodi, T. Saha *et al.* (2021): "Protective measures are associated with the reduction of transmission of Covid-19 in Bangladesh: A nationwide cross-sectional study." *PLoS One* **16(11)**: p. e0260287.

Shi, P., Y. Dong, H. Yan, C. Zhao, X. Li, W. Liu, M. He, S. Tang, & S. Xi (2020): "Impact of temperature on the dynamics of the Covid-19 outbreak in China." *Science of the total environment* **728**: p. 138890.

Spruance, S. L., J. E. Reid, M. Grace, & M. Samore (2004): "Hazard ratio in clinical trials." *Antimicrobial agents and chemotherapy* **48(8)**: pp. 2787–2792.

Stanley, T. D. (2005): "Beyond publication bias." *Journal of economic surveys* **19(3)**: pp. 309–345.

Stanley, T. D., S. B. Jarrell, & H. Doucouliagos (2010): "Could it be better to discard 90% of the data? A statistical paradox." *The American Statistician* **64(1)**: pp. 70–77.

Steel, M. F. (2020): "Model averaging and its use in economics." *Journal of Economic Literature* **58(3)**: pp. 644–719.

Sugimura, M., O. Chimed-Ochir, Y. Yumiya, H. Ohge, N. Shime, T. Sakaguchi, J. Tanaka, T. Takafuta, M. Mimori, M. Kuwabara *et al.* (2021): "The association between wearing a mask and Covid-19." *International Journal of Environmental Research and Public Health* **18(17)**: p. 9131.

Toyokawa, T., T. Shimada, T. Hayamizu, T. Sekizuka, Y. Zukeyama, M. Yasuda, Y. Nakamura, S. Okano, J. Kudaka, T. Kakita *et al.* (2022): "Transmission of SARS-CoV-2 during a 2-h domestic flight to Okinawa, Japan, March 2020." *Influenza and Other Respiratory Viruses* **16(1)**: pp. 63–71.

Ueki, H., Y. Furusawa, K. Iwatsuki-Horimoto, M. Imai, H. Kabata, H. Nishimura, & Y. Kawaoka (2020): "Effectiveness of face masks in preventing airborne transmission of SARS-CoV-2." *mSphere* **5(5)**: pp. e00637–20.

Van Dyke, M. E., T. M. Rogers, E. Pevzner, C. L. Satterwhite, H. B. Shah, W. J. Beckman, F. Ahmed, D. C. Hunt, & J. Rule (2020): "Trends in county-level Covid-19 incidence in counties with and without a mask mandate, Kansas, June 1–August 23, 2020." *Morbidity and Mortality Weekly Report* **69(47)**: p. 1777.

Venugopal, U., N. Jilani, S. Rabah, M. A. Shariff, M. Jawed, A. M. Batres, M. Abubacker, S. Menon, A. Pillai, N. Shabarek *et al.* (2021): "SARS-CoV-2 seroprevalence among health care workers in a New York City hospital: A cross-sectional analysis during the Covid-19 pandemic." *International Journal of Infectious Diseases* **102**: pp. 63–69.

Wang, Q., X. Huang, Y. Bai, X. Wang, H. Wang, X. Hu, F. Wang, X. Wang, J. Chen, Q. Chen *et al.* (2020a): "Epidemiological characteristics of Covid-19 in medical staff members of neurosurgery departments in Hubei province: A multicentre descriptive study." `https://doi.org/10.1101/2020.04.20.20064899`.

Wang, X., Z. Pan, & Z. Cheng (2020b): "Association between 2019-nCoV transmission and N95 respirator use." *Journal of Hospital Infection* **105(1)**: pp. 104–105.

Wang, Y., H. Tian, L. Zhang, M. Zhang, D. Guo, W. Wu, X. Zhang, G. L. Kan, L. Jia, D. Huo *et al.* (2020c): "Reduction of secondary transmission of SARS-CoV-2 in households by face mask use, disinfection and social distancing: A cohort study in Beijing, China." *BMJ global health* **5(5)**: p. e002794.

Wilson, N., G. Marks, A. Eckhardt, A. Clarke, F. Young, F. Garden, W. Stewart, T. Cook, & E. Tovey (2021): "The effect of respiratory activity, non-invasive respiratory support and facemasks on aerosol generation and its relevance to Covid-19." *Anaesthesia* **76(11)**: pp. 1465–1474.

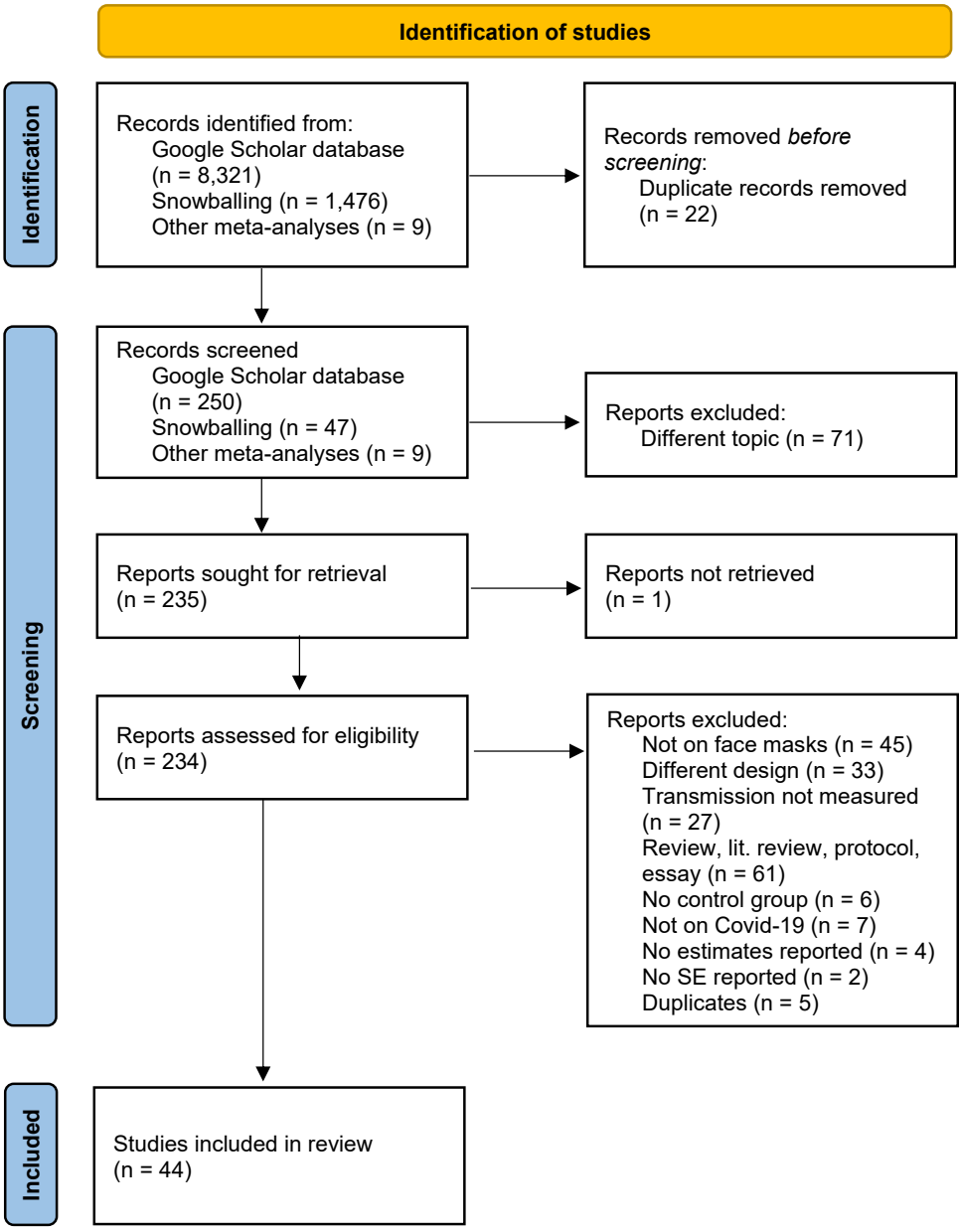
World Health Organisation (2022): "Who coronavirus (Covid-19) dashboard overview." `https://covid19.who.int/`, Last accessed on 2022-12-29.

Xiao, M., L. Lin, J. S. Hodges, C. Xu, & H. Chu (2021): "Double-zero-event studies matter: A re-evaluation of physical distancing, face masks, and eye protection for preventing person-to-person transmission of Covid-19 and its policy impact." *Journal of Clinical Epidemiology* **133**: pp. 158–160.

Zhang, J. & K. F. Yu (1998): "What's the relative risk? A Method of correcting the odds ratio in cohort studies of common outcomes." *JAMA* **280(19)**: pp. 1690–1691.

A Details of literature search

Figure 6: PRISMA flow diagram



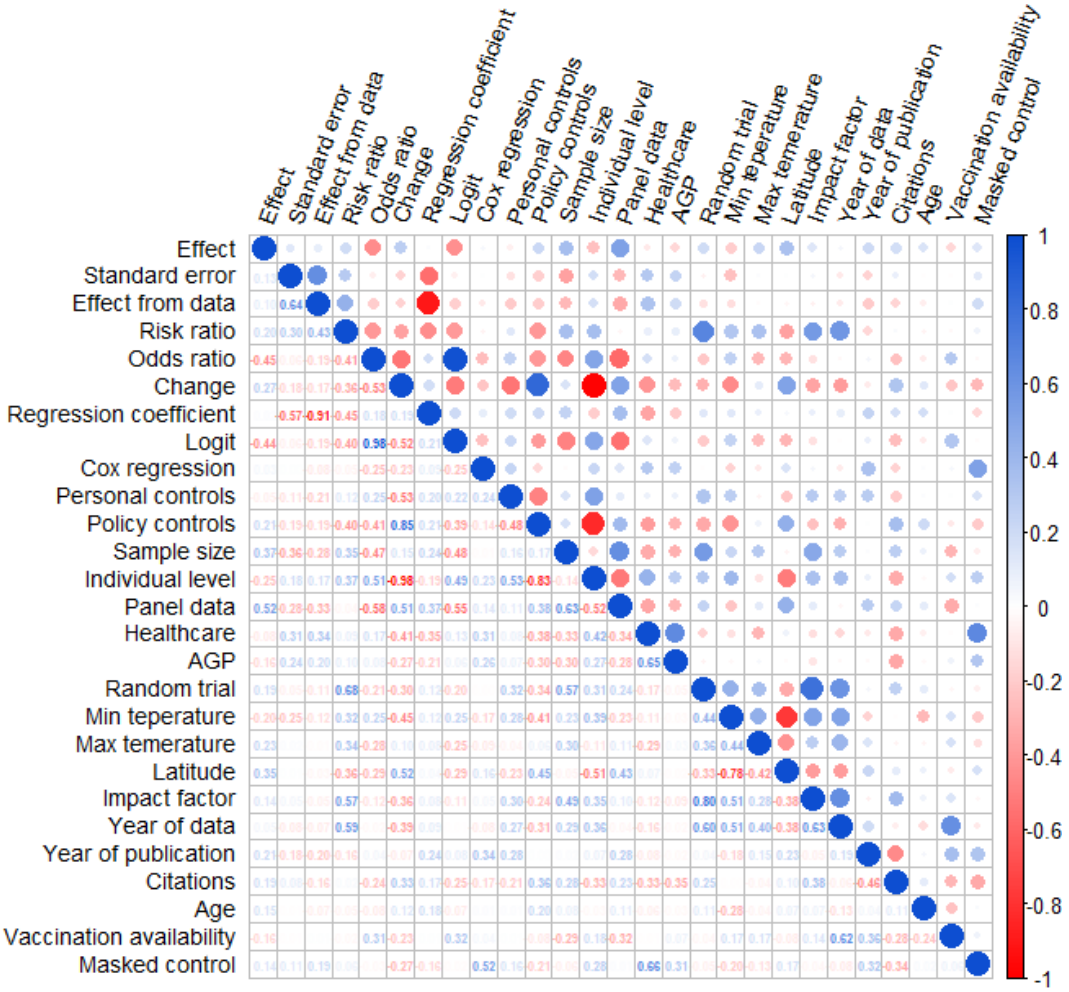
Note: The following query was used to search the studies in the Google Scholar database. ("SARS-CoV-2" OR "2019-nCoV" OR "coronavirus" OR "COVID-19") respirator transmission (observational OR descriptive OR case-control) face mask respirator epidemiological -meta. The search was performed on the 2nd of February. The studies were examined based on the abstract, brief overview of the study and/or quick inspection of the methods and results section. The search was restricted to include only studies since 2019. The diagram was created based on the template by Page *et al.* (2021). PRISMA = Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Table 7: Studies identified for analysis

Author (year)	
Abaluck *et al.* (2022)	Khalil *et al.* (2020)
Akinbami *et al.* (2020)	Li *et al.* (2021)
Andrejko *et al.* (2022)	Lio *et al.* (2021)
Budzyn *et al.* (2021)	Loeb *et al.* (2022)
Bundgaard *et al.* (2021)	Maltezou *et al.* (2020)
Davido *et al.* (2021)	Martischang *et al.* (2022)
Dörr *et al.* (2022)	Mitze *et al.* (2020)
Doung-Ngern *et al.* (2020)	Nelson *et al.* (2021)
Fawcett *et al.* (2023)	Nguyen *et al.* (2020)
Fletcher *et al.* (2022)	Payne *et al.* (2020)
Gonçalves *et al.* (2021)	Piapan *et al.* (2020)
Guo *et al.* (2020)	Pienthong *et al.* (2022)
Guy Jr *et al.* (2021)	Rebmann *et al.* (2021)
Haller *et al.* (2022)	Sharif *et al.* (2021)
Heinzerling *et al.* (2020)	Sugimura *et al.* (2021)
Chatterjee *et al.* (2020)	Toyokawa *et al.* (2022)
Chen *et al.* (2020)	van den Broek-Altenburg *et al.* (2021)
Chernozhukov *et al.* (2021)	Van Dyke *et al.* (2020)
Jehn *et al.* (2021)	Venugopal *et al.* (2021)
Joo *et al.* (2021)	Wang *et al.* (2020a)
Kahlert *et al.* (2021)	Wang *et al.* (2020b)
Karaivanov *et al.* (2021)	Wang *et al.* (2020c))

B Correlation coefficients table

Figure 7: Correlation table for all eligible variables



Note: The figure shows the correlation coefficients for all variables eligible for BMA, only 18 of these 27 variables were selected for the final model.

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