Does face mask use elicit risk-compensation? Quasi-experimental evidence from Denmark during the SARS-CoV-2 pandemic

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Abstract

Background: Public use of face masks has been widely adopted to halt the SARS-CoV-2 pandemic but a key concern has been whether the effectiveness of face mask use is limited due to the elicitation of false feelings of security that decrease the observance of other protective behaviors, so-called risk-compensation.

Methods: We exploit quasi-experimental variation, prompted by three major changes in policy, to assess whether public use of face masks elicit risk-compensation by increasing the number of close contacts or decreasing attention to distancing and hygiene measured in daily nationally representative surveys (N = 106,880).

Results: Number of close contacts: Face mask use prompted by the policy changes decrease the number of contacts in two of the three interventions. In the remaining intervention, it has no effect. Attention to hygiene: Across the changes face masks use does not affect people's attention to hygiene. Attention to distancing: In two of three interventions, face mask use increase attention to distancing. In the remaining intervention, we see a decrease in attention.

Conclusions: Overall, face mask may occasionally elicit a narrow form of risk-compensation; specifically, reducing engagement in physical distancing. However, such narrow forms of risk-compensation are limited: The results do not reveal any effects on the actual number of physical contacts, only on the psychological attention to distancing advice. Moreover, the negative effect only appears for one of three interventions. The other two interventions suggest that face mask use *increases* attention to physical distancing.

Keywords

Face masks; Risk-compensation; Quasi-experiment

Introduction

To contain the SARS-CoV-2 pandemic, the WHO has encouraged the general use of facial masks in settings with "widespread community transmission" and "where physical distancing cannot be maintained".¹ Nonetheless, a number of countries have been reluctant to adopt this policy, questioning the efficacy of facial masks as a protective device for the general public², and some, e.g., the Scandinavian countries, observed very low usage of face masks in the initial phases of the pandemic.³ The discussion has focused on whether the effectiveness of the public's use of facial masks is a function of features beyond their mechanical ability to filter viral particles; in particular, whether and how mask use shapes the behavior of the wearer and bystanders, respectively.^{4,5} Concerns have been raised that the effectiveness of masks may be reduced by generating a "false sense of security" or what is often in the psychological literature referred to as risk-compensation, i.e., that the adoption of one precautionary measure down-regulates feelings of threat, which in turn elicits more risky behavior.^{5,6}

There are only a few studies on the effectiveness of public mask use during the SARS-CoV-2 pandemic. These suggest that public use of face masks is efficient to decrease infection spread despite potential dynamics related to risk-compensation.⁷ Furthermore, randomized controlled experiments suggest that mask use does not lead bystanders to engage in risk-compensation.^{8,9} Simultaneously, we know virtually nothing about the key concern from a risk-compensation perspective⁵: If and how mask use shapes the behavior of the wearers themselves? One review of studies outside of the SARS-CoV-2 pandemic finds evidence that mask-wearing does not decrease focus on hand hygiene.⁶ Three studies that combine quasi-experimental variation in mask use and aggregated mobility data show mixed evidence on the impact of mask use on physical distancing. While two of the studies find no effect,^{10,11} the third finds that the average person in US states with face mask mandates spent 20-30 minutes less time at home, and increased visits to a number of commercial locations, following the

mandate.¹² Correlational studies find that the motivation to use masks is positively associated with the motivation to keep distance to others, avoiding handshakes, and washing of hands.^{13,14} However, these studies are either based on limited research designs^{13,14} that prevent them from isolating the independent effects of mask use from a plethora of confounding factors or limited data¹⁰⁻¹² that keep them from moving beyond aggregated to individual-level data.

We examine risk-compensation using individual-level analyses with causal leverage and ask: Do policies that promote the general use of face masks in public settings increase mask-wearers' tendency to seek out such settings, i.e., engage in risk compensation? Ethical concerns over randomizing access to mask protection during a pandemic, as well as the potentially high risk of non-compliance, imply that we have to rely on observational designs to analyze this research question. This raises fundamental challenges pertaining to causality. Perhaps the most obvious challenge is the concern over reverse causality. For example, the WHO recommends the use of masks in public settings where distance cannot be maintained. Accordingly, even a non-risk-compensating use of masks would imply a positive association between mask use and visiting crowded places. Therefore, it is key to determine whether the promotion of masks makes people more likely to use masks in crowded settings that they would visit in any case; or whether people are more likely to visit crowded settings upon the promotion of masks.

We discern between these potential effects of mask-usage on the behavior of the wearer by utilizing three major changes in the policies regarding mask use in Denmark . We utilize a unique survey study with daily, large-scale representative surveys of Danes during the SARS-CoV-2 pandemic (N=106,880). First, we demonstrate how face mask use correlates with other individual-level protective behavior indicators. Second, we conduct an intervention analysis that exploits quasi-experimental variation in face mask usage induced by the Danish policy changes.

Methods

Data

Until July 31 2020, the Danish health authorities only recommended the use of masks under special circumstances.^{15,16} From August 22 (announced on August 15), this recommendation was changed mandating face mask use *at all times* in public transportation. From September 17 (announced on September 15), the policy was expanded to also include bars and restaurants. Finally, from October 29 (announced on October 23), the government further expanded the policy to include *all indoor locations with public access* (e.g., supermarkets).

Our survey data is collected by Kantar Gallup. We collect approximately 500 respondents each day. As we started surveying the use of face masks from July 20, all analyses in this study are based on data from July 20 until December 31 (N = 106,880). Participants are Danish citizens aged 18 or older. They are recruited using stratified random sampling—on age, sex, and geography—based on the entire database of Danish social security numbers. The recruited participants are thus representative of the broader Danish population in regards to these characteristics. The response rate is 25 percent. We did not employ any monetary incentives for participation. Participants are invited to take the survey via eBoks (the official electronic mail system used by the authorities and other institutions to communicate with citizens). Note that about 8 percent of the Danish population, mainly older people, are exempt from eBoks. Nonetheless, we observe that the sampled observations are very close to the population margins with respect to sex, age, and education (see table S.1 in the SI). Therefore, we conduct the main analyses using the unweighted data. However, we provide robustness analyses that use post-stratification weights to adjust the final sample data to fit the demographic margins with respect to sex, age, and geography. All the main analyses replicate (see Figure S.4).

Measures

All measures are self-reported. The key measures are mask use, contact behavior, distance attention, and hygiene attention. Mask use is measured by a single question, while the remaining protective behaviors are measured using indices. Questions, values, descriptives, and scale reliabilities are provided in Table 1. Participants who answered that they used a mask one or more times within the last week are classified as a mask-user. Before adding together each of the contact measures into the overall contact index, we ceil off each of the underlying measures at the 99th percentile to control the influence of outlying observations. On the remaining indices, we add together the individual questions into reliable scales of the underlying protective behaviors. “Do not know” answers are classified as missing. In the table below, we report the mean and standard deviation based on the unstandardized measures. In the statistical analyses, we center each of the indices on their mean and standardize them with a standard deviation of 1.

[Table 1 about here]

The analyses also include a set of sociodemographic variables: Age, gender, education, and municipality of residence. We also include a measure of threat appraisal, indicating to what degree participants feel that the corona virus threatens them personally and to what degree they feel it is a threat to society. In addition, we include day of the week and the epidemic development. For measurement descriptions, see Table S.2.

Design and estimation

We first develop a multilevel regression model to analyze whether the correlations between face mask use and other types of protective behaviors are indicative of potential risk-compensation. The model allows the intercepts and slopes of each correlate to vary with the changes in Danish face mask policy. This means that we specify four periods, corresponding to the three policy changes discussed above.. As the observations are also nested in days, we accordingly allow the intercepts and slopes to also vary by day. In the results section, we present three models that in turn include each behavioral correlate. We also present results from a demographics-only model in the SI (see Section S.2).

The use of face masks is by no means random. Accordingly, comparisons of protective behavior between mask-users and non-mask-users are biased by selection into each group. We rely on exogenous variation in mask use prompted by the three changes in face mask policy to address this selection problem. Specifically, we view the changes in policy as *exogenous encouragements* for people to wear masks.¹⁷

Within this framework, we define four types of people: “compliers”, “always-takers”, “never-takers”, and “defiers”. Our estimator focuses on compliers, i.e., people who did not use masks prior to the changes in policy, but take up mask use after the policy changes. The remaining three types of people denote non-compliers (see Section S1.5 for a detailed discussion). The estimator addresses the non-compliance by scaling the so-called intention-to-treat (ITT) effects—i.e., the covariate-adjusted difference in outcomes between people observed before and after the mask policy changes—by the fraction of compliers to isolate the local average treatment effect of mask use among *compliers*.¹⁷ (See Section S1.2 for a detailed discussion of this estimator).

This analytical strategy makes three identifying assumptions. First that the policy instruments significantly increase the use of face masks (i.e., a strong first-stage). The upper panel of Figure 1 shows that this is in fact the case: We observe that the indicator for mask use

(the solid black line) increases substantially across the policy thresholds (vertical dashed lines). Second, the estimator assumes monotonicity (i.e., the absence of “defiers”). This assumption would be problematic if some people stopped wearing masks after the policies changed, but would have worn masks in the absence of changes. Empirically, Figure 1 shows that mask use increase monotonously over time, corroborating the assumption.

[Figure 1 about here]

Third, the key assumption is that both the *potential* use of masks and the *potential* protective behavior outcomes are independent from the *timing* of the policy instruments, implying that the policy changes can have no effect on protective behaviors beyond their effects on mask use. A key concern is whether the severity of the SARS-CoV-2 epidemic simultaneously determines the policy changes and have independent effects on the protective behavior outcomes. From a substantive perspective, we can expect that the timing of the policies were exogenous to the incidence rate because the changes were announced abruptly and with short implementation periods.

Building on this logic, we eliminate biases from differences in epidemic severity as we focus the estimations on a narrow bandwidth around each policy threshold. In our benchmark results, we include observations within ± 14 days from each threshold, but we show that our benchmark results are essentially identical when zooming in on the thresholds. The lower panels of Figure show that the epidemic (red bars) develops smoothly over each of the face mask policy thresholds (indicated by the dashed vertical lines). Altogether, this alleviates concerns that the analytical strategy is biased by differences in epidemic development and corroborates the key identifying assumption.

Another concern is that the changes in policy have effects on the outcomes outside their impacts on mask use. Most prominently, the changes may take effect through increased feelings of threat. Alternatively, the policies might also change the composition of those who use masks such that it might be compositional differences that explain changes in protective behavior. To account for such potential biases, we rerun all analyses while including threat appraisal and the battery of demographic covariates. In addition, we also include day of the week and daily new confirmed cases in these estimations. All results replicate (see Figure S.5).

Results

Figure 2 displays the developments in the correlations between mask use and each of the other protective behaviors (Table S.2 reports the supporting regression table). The figure shows that the overall correlations (red horizontal lines) between mask use and each protective behavior measure are relatively similar. A one standard deviation increase in contacts is associated with about a 2 percentage points increase in the likelihood of wearing a mask ($\beta_{\text{contact}} = 0.0194$, $z = 2.72$). A one standard deviation increase in hygiene attention is associated with about a 3 percentage points increase in mask use ($\beta_{\text{hygiene}} = 0.0321$, $z = 5.28$), while a standard deviation increase in distance attention is associated with about a 2 percentage points increase ($\beta_{\text{distance}} = 0.0155$, $z = 2.74$). Moreover, the figure also shows that these correlations are not time-invariant. Instead, we observe that the total correlations (orange filled circles) systematically slope downwards over time as captured by the lowess curves (solid orange lines).

[Figure 2 about here]

Figure 3 presents the results from the intervention analysis strategy. The upper-left panel displays the benchmark estimates (Table S.3 reports the supporting regression table).

Focusing on the public transportation intervention, the benchmark estimates show that mask use has no effect on the number of contacts ($\beta_{\text{contact}} = -0.0472, z = -0.43$) and hygiene attention ($\beta_{\text{hygiene}} = 0.0750, z = 0.82$). To the contrary, mask use decreases distance attention : Mask users are about 0.35 standard deviations less attentive to distancing compared to non-mask users ($\beta_{\text{distance}} = -0.3701, z = -3.86$). Moving to the restaurants and bars intervention, the benchmark estimates show that mask use decrease the number of contacts ($\beta_{\text{contact}} = -0.6109, z = -6.19$), increase distance attention ($\beta_{\text{distance}} = 0.7836, z = 8.15$), and has no effect on hygiene attention ($\beta_{\text{hygiene}} = 0.1497, z = 0.087$). Finally, the empirical pattern around the general mask mandate is consistent with the latter results: Face mask use decrease the number of contacts ($\beta_{\text{contact}} = -0.5063, z = -4.14$), increase distanceattention ($\beta_{\text{distance}} = 0.9780, z = 7.02$), but has no effect on hygiene attention ($\beta_{\text{hygiene}} = 0.1938, z = 0.16$).

[Figure 3 about here]

Consistent with the key identifying assumption, including the battery of covariates into the estimations does not fundamentally change the findings (see Figure S.5). Similarly, the upper-right and lower panels show a high degree of stability in the estimates as we vary the width of the estimation. Given that we eliminate biases from differences in epidemic severity as we limit the bandwidth this further corroborates the design-based identification. We probe the robustness of the results further in a range of sensitivity tests in the SI (see Figures S.6-S.11).

Discussion

Does face mask use facilitate false feelings of safety that decreases the observation of other key protective advice, so-called risk compensation? We demonstrate that mask use *overall*

correlates positively with the observed protective behaviors. Our analyses simultaneously show that the correlations are largest in the beginning of the study period and drop towards zero over time with the onset of the face mask policies. The correlational findings provide mixed evidence for the risk-compensation hypothesis. On the one hand, both the positive overall correlations between mask use and attention to hygiene and distancing and the decrease in the correlation between number of contacts and face mask use over time speak against widespread risk-compensating behavior. These findings are consistent with a review of studies outside the SARS-CoV-2 pandemic, which finds that mask-wearing does not decrease focus on hand hygiene.⁶ They also align with correlational evidence from studies within the SARS-CoV-2 pandemic that, among Germans and Chinese, have found that the motivation to use masks is positively associated with the motivation to keep a distance to others, avoiding handshakes, and washing of hands.^{13,14}

On the other hand, the data also demonstrates that face mask users *overall* engage in more contacts and that the association with distance and hygiene attention decrease towards zero over time. This may be interpreted as consistent with the risk-compensation perspective that mask use creates a false sense of security that in turn makes people less likely to observe other protective behaviors. Alternatively, it might show that masks are used as intended: They wear masks as a precautionary measure when they cannot avoid contact and keep the advised distance.

Ultimately, the question of risk-compensation depends on the causal direction in these correlations. To gauge this question, we utilized quasi-experimental variation in face mask use prompted by the three changes to Danish face mask policy. Altogether, the findings from these analyses speak against broader forms of risk-compensation related to the use of face masks. Focusing on the number of contacts, we find that increased mask use prompted by the restaurants and bars policy expansion and the general public space expansion decreases the

number of contacts, while we see no effect related to the public transport policy change. Focusing on hygiene attention, we find no effect of mask use across either of the three changes to policy. These results are in line with the correlational results from previous studies discussed above,^{13,14} but they are also consistent with two studies that exploit quasi-experimental variation in mask use prompted by differences in policy to show that increased mask use do not have an impact on social distancing at the aggregate level.^{10,11}

Moving to the question of distance attention, the causal results are mixed. Mask use prompted by the public transport policy change elicited a decrease in attention, whereas mask use stimulated by the restaurants and bars expansion and the general public space expansion increased attention. Taken together, there is little evidence for risk-compensation as a general phenomenon. However, the finding of a decrease in attention to distancing in relation to the first policy change follows the findings of another previous study that showed that the average American in states with face mask mandates at the aggregate spent less time at home and increased their visits to a number of commercial locations, following the mandate.¹²

Overall, these results suggest that face masks may occasionally elicit a narrow form of risk-compensation; specifically, reducing engagement in physical distancing. This conclusion is, however, qualified by two important observations. First, such narrow forms of risk-compensation are limited: The results do not reveal any effects on the actual number of physical contacts, only on the psychological attention to distancing advice. Second, the negative effect only appears for one of three interventions. The other two interventions suggest that face mask use *increases* attention to physical distancing.

It is important to note limitations in regards to these conclusions. First, while the data are randomly sampled from a national registry, the response rate was about 25 percent and was sent via the national electronic message system. All Danes have access to this system, but the less digitized may not see and respond to invitations. Second, there are no established measures

in Danish that assess compliance with pandemic advice. The present measures were developed by matching individual items to the phrasing of official advice from the Danish health authorities. However, the measures of contact behavior are in line with similar questions used in multiple countries for epidemic modelling purposes.¹⁸ Third, all measures are self-reported. Prior research suggests that behavioral self-reports during the pandemic are not strongly affected by social desirability bias¹⁹ but may suffer from well-known survey biases such as anchoring effects. Such biases do not disturb our estimations as long as they biases are constant within examined time windows. Fourth, the present data do not reveal the exact individual-level mechanism underlying the results. The challenge is that the data do not contain the specific location of the mask use or whether respondents wore masks for a specific social interaction. At the individual level, relationships may reflect that mandatory policies change people's tendency to seek out the specific location in which face masks are made mandatory but it can also reflect a variety of alternative individual-level effects. For example, the decrease in social contact among mask wearers revealed in two of the interventions could reflect that the use of face masks in the mandatory locations serve as reminders of health advice, which motivates mask wearers to not seek out other locations where mask usage is not mandatory. Fifth, we are not able to pinpoint why one intervention led to narrow risk-compensation, while two others had the opposite effect. However, in this regard is relevant to note a selection issue that we are not able to handle with the present identification strategy: The introduction of other interventions simultaneously with the mask interventions. With respect to the first intervention, nothing else was changed. Together with the second intervention, the government introduced a limited set of restrictions such as limiting the opening hours of bars. Together with third intervention, a change in the limitation on gatherings from 50 to 10 was introduced. These simultaneous interventions are likely to explain some of the negative effects of the second and third interventions on, for example, the number of contacts. Yet, even if this accounts for a

majority of the effect, the present results still document that risk-compensation is negligible enough to not offset these other protective effects. Furthermore, with respect to the third intervention, the other restrictions were implemented October 26, making it less likely that they bias the estimates as they are centered around October 29.

Finally, it is important to note that our findings are mute with regards to how effective face masks are in the management of epidemics. Answering this question requires a multidimensional assessment that relates to both the effectiveness of masks in filtering out viral particles, current infection rates, and the impact of face mask usage on human behavior. The present study exclusively assessed the latter component. Overall, our findings suggest that the adverse behavioral effects of face mask usage are negligible.

Tables and Figures

Table 1: Main measures in the study

	Questions	Values	Mean/SD/scale reliability
Mask use	How many times have you used a face mask within the last week?	1. I have not used a face mask 2. 1-3 times 3. 4-6 times 4. 7-9 times 5. 10 times or more	0.34/0.47/NA
Contact behavior	We are interested in hearing how many other people you have been physically close to in the past 24 hours. Physically close is here understood to be closer than 1 meters for at least 15 minutes. Please give us your best guess. <ul style="list-style-type: none"> • How many from your family, which you do not live with, have you been physically close to? • How many colleagues have you been physically close to? • How many friends and acquaintances (i.e., people you know the name of) have you been physically close to? • How many have you been physically close to that you didn't already know? (for example, in public transport, in playgrounds, in supermarkets) 	Numeric	6.68/12.08/0.47

Distance attention	To what degree did you yesterday pay attention to...? • Avoid physical contact. • Keep away from elderly and chronically ill people. • Keep 1-2 meters distance to other people. • Minimize going to places, where many people typically are going. • Minimize activities where you have contact to other people.	1. Not at all 2. 3. 4. 5. 6. 7. To a high degree 8. Don't know	5.47/1.26/0.84
Hygiene attention	To what degree did you yesterday pay attention to to..? • Ensure good hand hygiene by washing your hands frequently or using hand sprays. • Ensure frequent and thorough house cleaning. • Cough or sneeze in your sleeve.	1. Not at all 2. 3. 4. 5. 6. 7. To a high degree 8. Don't know	6.00/1.00/0.62

Note: Scale reliability is measured by α . NA=not applicable.

Figure 1: Analytical setup

Note: Top panel: Solid black line is the development in the indicator for mask use, while stacked bars show the development in the distribution. Lower panels: Red bars are confirmed cases. Vertical dashed lines are the policy thresholds.

Figure 2: Behavioral correlates of mask use

Note: The red horizontal lines indicate the *overall* associations between mask use and each of the correlates. The orange filled circles are the *total* correlations that combine the overall and random correlation parameters to test whether the associations vary over time. The solid orange line is a lowess smoother that describes the trend in the total correlations. The boxes show the distribution of correlations within each policy period (horizontal bars are the lower quartiles, medians, and upper quartiles; black Xs' display the means; and whiskers are 1.5 interquartile range from the quartiles). When estimating the correlations between the behavioral variables and mask use, we include the demographics in the fixed part of the multilevel regression models. The size of the estimated

coefficients reflect the change in mask use corresponding to a standard deviation change in each of the behavioral correlates, respectively.

Figure 3: Estimated effects of mask use on protective behaviors

Note: Estimates for public transport policy (orange filled squares), restaurants and bars policy (filled dark blue circles), and general public policy (green filled triangles). 95 % confidence intervals. Robust standard errors. Upper-left panel: Benchmark estimates include observations ± 14 days of each of the policy thresholds. N (public transport policy) = 18,377; N (restaurants and bars policy) = 19,694 ; N (general public policy) = 18,832. Remaining panels display effect estimates as we vary the estimation window. Effect estimates should be interpreted in standard deviation changes in the protective behavior measures.

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Conflicts of interest

There are no conflicts to report.

Key-points

- Unique evidence on risk-compensating behavior in a sample approximately 500 unique respondents each day in Denmark ($N = 106,880$).
- To gauge the question of causality, we utilized quasi-experimental variation in face mask use prompted by changes to Danish face mask policy.
- No evidence for broad forms of risk-compensation: Face mask use did not induce more risky behavior in domains beyond their usage such as attention to hygiene or close contacts with, e.g., family and friends.

- We did find that face mask use decreased peoples' attention to the avoidance of settings involving many individuals, but only with respect to one of three reforms.

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Data sharing: Data collected for this study as well as codebooks and analysis files will be made publicly available to others via Open Science Framework upon the publication of this article.

Supplementary Information

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S1 Methods and materials

In this section of the SI, we provide supplementary information pertaining to the discussions in the main manuscript about the methods and materials. First, we supply an overview of the covariates in the study. Second, we discuss the identification strategy in more detail.

S1.1 Measurements of covariates

Table S.1: Covariates in the study

	Questions	Values	Sample mean	Population mean
Age	How old are you?	Numeric	48.70	49.52
Gender	Are you?	0 = Male 1 = Female	0.50	0.51
Education	<p>What is your highest completed education?</p> <p>Holds information corresponding to Danish applicable categories:</p> <ol style="list-style-type: none"> 1. Elementary school 2. High school 3. Vocational training 4. Short-cycle tertiary 5. Medium-cycle tertiary 6. Bachelor's degree or equivalent 7. Master's degree or more <p>In the coding of the education indicator variable, we collapsed categories 1-3 into non-tertiary education (corresponding to ISCED categories 0-4) and categories 4-7 into tertiary education (corresponding to ISCED categories 5-8).</p>	0 = non-tertiary education 1 = tertiary education	0.51	0.55
Threat appraisal	<p>To what degree do you feel, that</p> <ul style="list-style-type: none"> • You are exposed regarding the Corona virus? • The Corona virus is a threat to Danish society? <p>We add these two questions together into our threat appraisal covariate.</p>	1. Not at all 2. 3. 4. 5. 6. 7. To a high degree 8. Don't know	4.15	NA
Municipality	Administrative information supplied by Danish statistics about each participants municipality of residence (there are 98 municipalities in Denmark)	NA	NA	NA
New confirmed cases	Data supplied by the Danish Center for Disease Control (SSI).	Numeric	896.61	896.61
Day of the week	Indicator variable for day of the week	1-7	NA	NA

Note: Sample and population means cover the adult (18+ years old) Danish population. NA: not applicable.

S1.2 Identification strategy

We address the selection issues relying on exogenous variation in mask use prompted by the change in face mask policy. In particular, we rely on the framework developed by Angrist et al. (1999) that allows for heterogeneous treatment effects. Hence, we view the changes to face mask policy as exogenous encouragements for people to take up the use of masks. In light of this framework, we can define four types of people. “Compliers” are people who comply with the encouragement. In other words, people who did not use mask prior to the change in policy, but take up mask use after the policy change. “Always-takers” are people who always use masks regardless of the policy. “Never-takers” are people who never wear masks regardless of the policy. Finally, “defiers” are people who refuse to wear masks because of the policy (or insist to wear mask in the absence of policy). Our identification strategy addresses noncompliance by scaling the so-called intention-to-treat (ITT) effect—i.e., the (covariate-adjusted) difference in outcomes between people before and after the mandatory mask policy—by the fraction of compliers (the so-called compliance rate) to isolate the local average treatment effect (LATE) of mask use among compliers (Angrist et al., 1999).

The strategy makes three identifying assumptions. *First*, that the policy instruments significantly increase the use of face masks (called the first stage assumption). The upper panel of Figure S.1 illustrates that face mask use increases significantly across the policy thresholds (vertical dashed lines). As we discuss in the manuscript, we focus our benchmark estimates on a sample that includes observations ± 14 days of the respective policy thresholds, yielding a strong first-stages with F-statistics of 512, 515, and 834 for in. *Second*, the estimator also assumes monotonicity (i.e., the absence of defiers). This assumption would only be problematic if some people stopped wearing masks after the policies changed, but would have

worn masks in the absence of changes. Empirically, we see that mask use increase monotonously over time, corroborating the assumption.

Figure S.1: Analytical strategy

Note: Top panel: Solid black is the development in the indicator for mask use, while stacked bars show the development in the distribution. Lower panels: Red bars are confirmed cases. Dashed vertical lines are the policy thresholds.

Third, the key identifying assumption is that the *potential* use of masks and the *potential* protective behavior outcomes are independent from instrument assignment, implying also that the instrument can have no effect on protective behaviors except through its effect on mask use (i.e., the exclusion restriction). A key concern here is whether the severity of the SARS-CoV-2 epidemic provides an alternative path between the instrument and the protective behaviors. Hence, the face mask policy was changed in response to increases in the incidence

rate and the epidemic development might simultaneously be expected to have independent effects on the protective behaviors. However, the lower panels of Figure S.1 show that the epidemic develops smoothly over the face mask policy thresholds, implying that the *timing* of the instruments should be exogenous to the incidence rate. As we narrow the width of the estimation windows, we accordingly eliminate biases from differences in epidemic severity. We exploit this to show that our benchmark results are essentially identical when zooming in on the thresholds.

Another concern is that changes in policy have effects on the outcomes outside of their effects through mask use. Most prominently, the changes in policy might take effect through increased feelings of threat. We close this path by including threat appraisal as a covariate into the estimations. Additionally, we might worry that the interventions also brought about a change in the composition of people who wear masks. If this is the case, then compositional changes rather than mask use itself might explain potential effects. To account for these biases, we also include a battery of demographics into the estimation, including sex, age, education, and municipality of residence. All results replicate (see Table S.2 below for results).

S2 Supporting results: Correlational findings

In this section, we provide first the supporting regression table for the correlational results in the manuscript. Second, we discuss the supporting demographic results. Third, we show that the correlations remain substantively similar when replacing the continuous contact scale with a dummy that indicates whether or not the participant reports any infection-relevant contacts, corroborating the robustness of the results.

S2.1 Supporting regression table

Table S.2: Demographic and behavioral correlates of face mask use

	Model 1	Model 2	Model 3	Model 4
Fixed parameters				
<i>Behavioral</i>				
Contact behavior (1 sd)		0.019*** (0.007)		
Hygiene attention (1 sd)			0.032*** (0.006)	
Distance attention (1 sd)				0.016*** (0.006)
<i>Demographics</i>				
Female	0.020** (0.007)	0.018*** (0.002)	0.009*** (0.002)	0.016*** (0.002)
Age (1 sd)	-0.024** (0.009)	-0.017*** (0.001)	-0.026*** (0.001)	-0.023*** (0.001)
Education (tertiary)	0.014 (0.008)	0.016*** (0.002)	0.018*** (0.002)	0.015*** (0.002)
Constant	0.616*** (0.139)	0.614*** (0.141)	0.619*** (0.140)	0.619*** (0.139)
Random parameters:				
Policy periods				
Sd (Contact behavior)		0.014 (0.005)		
Sd (Hygiene attention)			0.012 (0.004)	
Sd (Distance attention)				0.011 (0.004)
Sd (Female)	0.013 (0.005)			
Sd (Age)	0.017 (0.006)			
Sd (Education)	0.015 (0.006)			
Sd (constant)	0.278 (0.098)	0.281 (0.099)	0.279 (0.099)	0.277 (0.098)
Random parameters:				
Day				
Sd (Contact behavior)		0.010 (0.002)		
Sd (Hygiene attention)			0.000 (0.000)	
Sd (Distance attention)				0.008 (0.004)
Sd (Female)	0.006 (0.0068)			
Sd (Age)	0.009 (0.002)			
Sd (Education)	0.000 (0.005)			
Sd (constant)	0.058 (0.004)	0.059 (0.003)	0.059 (0.003)	0.058 (0.003)
Observations	104,133	104,133	104,106	104,087

Notes: Unstandardized multilevel regression coefficients. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S2.2 Supporting demographic results

Focusing on the demographic correlates (Model 1 above), we see that females overall are about 1.5 percentage points more likely to wear masks compared to males ($\beta_{\text{female}} = 0.013$, $z = 2.96$). This correlation increases over the first two policy changes, and then decreases toward zero with the third change (see Figure S.3 below). Moving to the age correlation, a one standard deviation increase in age is overall associated with about a 2.5 percentage points decrease in the likelihood of wearing a mask ($\beta_{\text{age}} = -0.024$, $z = -2.72$). Here, we first see a decrease in the correlation with the onset of the first policy, and then an increase from the beginning of the second policy (see Figure S.3 below). The overall correlation between education and mask use is not statistically distinguishable from zero ($\beta_{\text{education}} = 0.014$, $z = 1.83$), but this reflects a significant amount of variation over time (see Figure S.3 below). In particular, we see that the correlation increases from about zero to about 0.03 in the third policy period. Then with the onset of the third policy change it drop toward zero in the fourth period.

Figure S.2: Demographic correlates of face mask use

Note: The red horizontal lines indicate the *overall* associations between mask use and each of the correlates. The orange filled circles are the *total* correlations that combine the overall and random correlation parameters to test whether the associations vary over time. The solid orange line is a lowess smoother that describes the trend in the total correlations. The boxes show the distribution of correlations within each policy period (horizontal bars are the lower quartiles, medians, and upper quartiles; black Xs' display the means; and whiskers are 1.5 interquartile range from the quartiles). The size of the estimated coefficients reported reflect the change in mask use corresponding to a standard deviation change in each of the behavioral correlates, respectively.

S2.3 Contacts modeled as an indicator (any contact vs. no contact)

We replace the continuous contact scale used in the main results with a dummy that indicates whether participants had any contacts or not. We see that the overall correlation is substantively similar to the main results, i.e., an estimate of 0.037 ($z = 3.08$) compared to the estimate in the main results of 0.019 ($z = 2.72$). Simultaneously, we also see a substantively similar development in the correlation over time: An upward shift with the onset of the first policy change that then drops with the second and third change toward zero.

Figure S.3: Any contacts vs. no contact

Note: The red horizontal line indicate the *overall* association between mask use and the contact indicator. The orange filled circles are the *total* correlations that combine the overall and random correlation parameters to test whether the associations vary over time. The solid orange line is a lowess smoother that describes the trend in the total correlations.

S3 Supporting results: Intervention analysis

In this section of the SI, we present the supporting results for the intervention analysis findings. First, we provide the supporting regression table for the benchmark estimates. Second, we provide a series of sensitivity analyses that probe the robustness of these findings, including (1) treating mask use as a continuous treatment, (2) replacing the policy instrument with the announcement of the face mask policy rather than the onset, (3) modeling the number of infection relevant contacts as a count variable, (4) modeling contact behavior as a dummy, indicating whether or not the individual had any infection relevant contacts or not, and (5) including in the model an additional battery of demographic controls. Finally, we display the results across the sub measures of each of the protective behavior scales.

S3.1 Supporting regression table for the benchmark estimates

Table S.3: Benchmark estimates, regression table

Outcome	Contacts			Distance			Hygiene		
Intervention	1	2	3	1	2	3	1	2	3
Mask use effect	-.0471 (.1093)	-.06109*** (.0988)	-.5063*** (.1223)	-.3701*** (.096)	.7836*** (.0962)	.9780*** (.1394)	.075 (.0912)	.1497 (.0874)	.1938 (.1382)
First-stage F-stat	512	515	834	512	515	834	512	515	834
Observations	18,377	19,694	18,832	18,377	19,694	18,832	18,377	19,694	18,832

Note: Estimated local average treatment effects among compliers. Robust standard errors in parentheses. Covariates: municipality of residence and threat appraisal. Estimates should be interpreted in standard deviation changes in the protective behavior outcomes.

S3.2 Robustness of the intervention analysis findings

S3.2.1 Weighted results

Figure S.4 show that the main results are essential identical when treating mask use as a continuous treatment rather than a dummy, indicating whether or not the participant has used a mask within the last week.

Figure S.4: Benchmark estimates, weighted

Note: Estimates for public transport policy (orange filled squares), restaurants and bars policy (dark blue circles), and general public policy (green filled triangles). 95 % confidence intervals. Robust standard errors. Estimates include observations ± 14 days of the policy thresholds. N (public transport policy) = 18,377; N (restaurants and bars policy) = 19,694; N (general public policy) = 18,832.

S3.2.2 Inclusion of covariates

Figure S.5 show the benchmark results upon inclusion of covariates (sex, age, education, municipality of residence, threat appraisal, confirmed daily cases, day of the week). Fundamentally, the results do not change, corroborating the identification strategy.

Figure S.5: Benchmark estimates, covariates

Note: Estimates for public transport policy (orange filled squares), restaurants and bars policy (dark blue circles), and general public policy (green filled triangles). 95 % confidence intervals. Robust standard errors. Estimates include observations ± 14 days of the policy thresholds. N (public transport policy) = 17,851; N (restaurants and bars policy) = 19,150; N (general public policy) = 18,287. Covariates: sex, age, education, municipality of residence, threat appraisal, confirmed daily cases, day of the week.

S3.2.3 Mask use as continuous treatment

Figure S.6 show that the main results are fundamentally similar when treating mask use as a continuous treatment rather than a dummy, indicating whether or not the participant has used a mask within the last week.

Figure S.6: Benchmark estimates, mask use treated as a continuous treatment

Note: Estimates for public transport policy (orange filled squares), restaurants and bars policy (dark blue circles), and general public policy (green filled triangles). 95 % confidence intervals. Robust standard errors. Estimates include observations ± 14 days of the policy thresholds. N (public transport policy) = 18,377; N (restaurants and bars policy) = 19,694; N (general public policy) = 18,832.

S3.2.4 Contact behavior modeled as count variable

Figure S.7 shows the estimated effects of mask use on the number of infection-relevant contacts, when modeled as a count using a IV gmm estimator. As we see, the findings are substantively similar to the main results.

Figure S.7: Contact benchmark estimates, modeled as a count variable

Note: Estimates for contacts modeled as a count. 95 % confidence intervals. Robust standard errors. Estimates include observations ± 14 days of the policy thresholds. N (public transport policy) = 18,377; N (restaurants and bars policy) = 19,694; N (general public policy) = 18,832.

S3.2.5 Contact behavior modeled as an indicator

Figure S.8 substitutes the continuous contact scale for a dummy that indicates whether the participant had any infection-relevant contacts or not. Conclusions remain unchanged.

Figure S.8: Benchmark estimates, modeled as an indicator

Note: Estimates for modeled as an indicator. 95 % confidence intervals. Robust standard errors. Estimates include observations ± 14 days of the policy thresholds. N (public transport policy) = 18,377; N (restaurants and bars policy) = 19,694; N (general public policy) = 18,832.

S3.3 Intervention results on sub measures of each protective behavior scale

Figures S.9-S.11 replicate the benchmark results of the manuscript while using each individual sub measure of the protective behavior scales as separate outcomes. Figure S.9 show that the estimated negative effects—related to the first intervention—on the distance attention scale is driven by the two sub measures that ask participants to what extent they yesterday were aware of: (1) minimize going to places where many people typically are going and (2) minimize activities where you have contact to other people. For contact behavior and hygiene attention, Figures S.10 and S.11 show that effects are substantively similar across all sub measures.

Figure S.9: Benchmark effect estimates on the sub measures of the distance attention scale

Note: Estimates for public transport policy (orange filled squares), restaurants and bars policy (dark blue circles), and general public policy (green filled triangles). 95 % confidence intervals. Robust standard errors. Estimates

include observations ± 14 days of the policy thresholds. N (public transport policy) = 18,377; N (restaurants and bars policy) = 19,694; N (general public policy) = 18,832.

Figure S.10: Benchmark effect estimates on the sub measures of the contact scale

Note: Estimates for public transport policy (orange filled squares), restaurants and bars policy (dark blue circles), and general public policy (green filled triangles). 95 % confidence intervals. Robust standard errors. Estimates include observations ± 14 days of the policy thresholds. N (public transport policy) = 18,377; N (restaurants and bars policy) = 19,694; N (general public policy) = 18,832.

Figure S.11: Benchmark effect estimates on the sub measures of the hygiene attention scale

Note: Estimates for public transport policy (orange filled squares), restaurants and bars policy (dark blue circles), and general public policy (green filled triangles). 95 % confidence intervals. Robust standard errors. Estimates include observations ± 14 days of the policy thresholds. N (public transport policy) = 18,377; N (restaurants and bars policy) = 19,694; N (general public policy) = 18,832.