Monitoring Public Behavior During a Pandemic Using Surveys: Proof-of-Concept Via Epidemic Modelling

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Abstract
Implementing a lockdown for disease mitigation is a balancing act: Non-pharmaceutical interventions can reduce disease transmission significantly, but interventions also have considerable societal costs. Therefore, decision-makers need near real-time information to calibrate the level of restrictions. We fielded daily surveys in Denmark during the second wave of the COVID-19 pandemic to monitor public response to the announced lockdown. A key question asked respondents to state their number of close contacts within the past 24 hours. Here, we establish a link between survey data, mobility data, and hospitalizations via epidemic modelling. Using Bayesian analysis, we then evaluate the usefulness of survey responses as a tool to monitor the effects of lockdown and then compare the predictive performance to that of mobility data. We find that, unlike mobility, self-reported contacts decreased significantly in all regions before the nation-wide implementation of non-pharmaceutical interventions and improved predicting future hospitalizations compared to mobility data. A detailed analysis of contact types indicates that contact with friends and strangers outperforms contact with colleagues and family members (outside the household) on the same prediction task. Representative surveys thus qualify as a reliable, non-privacy invasive monitoring tool to track the implementation of non-pharmaceutical interventions and study potential transmission paths.

Keywords: Epidemic monitoring, Mobility data, Survey data, Epidemic modelling
1 Introduction

Pandemic management is a balancing act. When an outbreak of infections flares up, governments and authorities need to impose restrictions and recommendations on society that are carefully calibrated to the situation. On the one hand, during the COVID-19 pandemic, such non-pharmaceutical interventions have considerable benefits by changing the dominant transmission route – close contacts between individuals – via the incentives and information they provide [1, 2]. On the other hand, these interventions have considerable costs in the form of negative externalities relating to the economy and mental health [3–5].

This balancing act puts authorities and governments in need of information to continuously calibrate the level of restrictions. It is not a matter of simply sending out a single set of instructions regarding restrictions and recommendations. Rather, authorities need to continuously receive information about the effectiveness of those restrictions and recommendations and adjust accordingly. An obvious source of information is directly related to the epidemic and includes the number of infection cases, hospitalizations, and deaths. Yet cases of infection are difficult to monitor and, for example, changes in the public’s motivation to participate in testing programs may create problems with respect to comparisons over time [6]. Furthermore, there is a significant lag between the onset of interventions and hospitalizations and death counts, which imply that it is difficult to calibrate interventions on the basis of such information. Consequently, researchers, authorities and governments worldwide have complemented epidemiological information with information on the direct target of the interventions: Behaviour [7, 8].

In this manuscript, we assess the predictive performance of a particular source of information about behavior during lockdowns: Population-based surveys on social contacts, fielded daily to representative samples of the Danish population during the COVID-19 pandemic (see Methods for details on this dataset). This assessment aligns with recommendations about the use of surveys as epidemic monitoring tools on the basis of experiences during the SARS epidemic in Hong Kong [9] and recommendations from the World Health Organization during the COVID-19 pandemic [10]. From a public health policy perspective, this particular dataset is a unique test case as it was, in fact, reported to the Danish government for this purpose on a twice-weekly basis during the second wave of COVID-19 infections in December 2020.

Furthermore, these data are unique in another respect: They constitute an open and ‘citizen science’ [11] alternative to the most used source of information on pandemic behavior: Mobility data. As we detail below, mobility data as a source of information may be problematic from both a methodological and policy perspective. Mobility data provides a proxy for close contacts between people and has been heavily utilized by researchers and public health institutions [8, 12–14]. Mobility data quantifies the population’s movement patterns and is unobtrusively obtained in a number of ways, for example, via people’s
smart phones and provided to researchers and governments via private companies such as Google [15]. This reliance, however, can and has raised concerns. First, in many cases, it implies that pandemic management and research relies on the willingness of private companies to share information during a critical crisis. Second, citizens themselves may be concerned about real or perceived privacy issues related to the sharing of data with authorities [16, 17]. Given the importance of public trust for successful pandemic management [18], such concerns – if widespread – can complicate pandemic control. Third, data from companies such as Google, Facebook and local phone companies may not be representative of the population of interest: The entire population of the country. Rather than being invited on the basis of traditional sampling methods, people opt-in to the services of different companies and, hence, the data from any single company is likely a biased sample. Fourth, the movements of people in society as captured by mobility data is only a proxy of the quantity of interest: Actual close encounters between individuals that drive the pandemic.

For these reasons, it is key to assess alternative sources of information about public behavior such as nationally representative surveys of the adult population. In principle, surveys could alleviate the problems relating to the collection and validity of mobility data. Survey research is a centuries old
low-cost methodology that can be utilized by public actors and that relies on well-established procedures for obtaining representative information on private behaviours in voluntary and anonymous ways [19].

At the same time, data from surveys come with their own methodological complications. As documented by decades of research, people may not accurately report on their own behaviour [20]. Survey answers during the pandemic may be biased by, for example, self-presentational concerns and inaccurate memory. While research on survey reports of behaviour during the pandemic suggests that self-presentational concerns may not affect survey estimates [21], memory biases may (although such biases are likely small for salient social behavior) [22]. Even with such biases, however, surveys may be fully capable to serve as an informative monitoring tool. The key quantity to monitor is change in aggregate behaviour over time. If reporting biases are randomly distributed within the population, aggregation will provide an unbiased estimate. Even if this is not the case, changes in the survey data will still accurately reflect changes in population behaviour as long as reporting biases are stable within the relevant time period.

On this basis, the purpose of the present manuscript is, first, to examine the degree to which survey data provide useful diagnostic information about the trajectory of behavior during a lockdown and, second, to compare its usefulness to information arising from mobility data. To this end, we focus on a narrow period around Denmark’s lockdown during the second wave of the COVID-19 epidemic in the Fall of 2020, i.e., prior to vaccine roll-out when it was crucial for authorities to closely monitor public behavior. We demonstrate the usefulness of survey data on a narrow window of time because the changing nature of factors such as seasonal effects, new variants, vaccines, changing masking efforts, etc., make it difficult to model COVID-19 transmission across long periods without making a large number of assumptions [6]. See also Sec. 3 for a discussion on the limitations of our survey data. In spite of the limited scope, we believe that the study remains relevant for policy makers because it allows to monitor public behaviour at a crucial moment, when policy makers should not be forced to rely on proximity or mobility data from private companies in the absence of timely incidence data.

Specifically, we ask whether a) daily representative surveys regarding the number of close social contacts and b) mobility data allow us to track changes in the observed number of hospitalizations in response to the lockdown. In addition, to further probe the usefulness of survey data, we provide a fine-grained analysis of how different types of social contacts relate to hospitalizations. Our results shed new light on the usefulness of survey data. Previous studies during the COVID-19 pandemic have documented high degrees of overlap between self-reported survey data on social behavior and mobility data, but have not assessed whether these data sources contain useful information for predicting transmission dynamics [23, 24]. One study did compare the predictive power of mobility data to survey data on the psychosocial antecedents of behavior [25] and found that mobility data was more predictive than the
survey data of COVID-19 transmission dynamics. Here, we provide a more balanced test by comparing the predictive value of mobility data and survey data when directly focused on self-reported behavior rather than simply its psychosocial antecedents.

2 Results

We establish the link between survey data, mobility data, and hospitalizations via state-of-the-art epidemic modeling, which uses the behavioural survey and mobility data as an input to capture underlying infectious activity [26, 27]. Specifically we extend the semi-mechanistic Bayesian model from Flaxman et al. [27, 28] to jointly model the epidemic spreading within the five regions of Denmark. Where possible, we use partial pooling of parameters to share information across regions and thus reduce region specific biases. We parametrize the regional reproduction number \( R_t \) with a single predictor \( X_t \) from our survey or the mobility data, respectively, for each realization of a model:

\[
\log(R_t) = \log(R_0) + eX_t \tag{1}
\]

The regional reproduction number at time \( t \) derives from the initial value \( R_0 \) and the scaled predictor \( eX_t \) with a logarithmic link-function (see Methods for full details on the model).

We compare the predictive performance of each data stream using leave-one-out cross-validation (LOO). LOO works by fitting the model to the observed hospitalizations excluding a single observation and comparing the prediction of the unseen observation against the observed real-world data. Repeating this process over all observations, allows one to estimate the model performance on out-of-sample data with a theoretically principled method that accounts for uncertainties [29]. In practice, this would result in an immense computational effort and therefore, we use an efficient estimation of LOO based on pareto-smoothed importance sampling [30]. In order to compare the predictive performance of, say self-reported survey against mobility, we calculate the LOO score for each model parametrization and consider the difference significant if it exceeds the 95% CI.

Because we are interested in the use of behavioural data as a guide for decision-making, our inference focuses on the key period of the second wave from 1-December-2020, i.e., about one week before Denmark’s lockdown announcement, to 20-February-2021 when vaccinations accelerated across the country. The period captures a sharp increase and eventual decline in hospitalizations during the second wave of Denmark’s Covid-19 pandemic (see Supplementary Fig. S1).
2.1 Defining risk-taking behaviour

As a monitoring tool, we first consider self-reported survey data on the daily number of contacts, defined as close encounters with less than 2 meters distance for at least 15 minutes [31]. The reported numbers are highly skewed, with 15.7% of all counts concentrated on zero with some reporting over 1 000 contacts (see Supplementary Fig. S2). As a result, taking the mean over daily reported numbers is highly sensitive to outliers, while reporting quantile-based measures obscure most of the variation.

Instead, we define the following robust measure of risk-taking behaviour: We label a participant in the survey as risk-taking if they report contacts above a fixed threshold and propose the daily fraction of risk-taking individuals as a predictor to the effective reproduction number. The intuition is that infections tend to be linked to large clusters via super-spreading events [32]. Therefore, we base our analysis on the fraction of the population that reports an above-average number of contacts.

That choice begs the question ‘What is a reasonable threshold that defines risk-taking behaviour?’ We choose a reference period prior to the lockdown’s announcement, take the distribution of contacts over the time window and define a range of thresholds in terms of percentiles (see Supplementary Fig. S2 for details). For a visual comparison, Fig. 1, second row illustrates the dynamics of risk-taking behaviour, referred to as self-reported survey data. The thresholds range from the 40th to the 90th percentile and translate into a critical number of contacts ranging from 3 and 25, respectively. For thresholds above the 60th percentile, risk-taking behaviour shows the strongest response to the announced lockdown and increases little during the Christmas period. Qualitatively, this behaviour matches the time-varying reproduction number $R_t$ (see Fig. 1, first row) that we inferred from national hospitalizations using a latent random-walk model (details in Sec. 4.2).

In the following, we use the 70th percentile as a threshold, which corresponds to 10 close contacts and more within the past 24h. However, our results are not sensitive to this value as all models within a threshold between the 60th and 90th percentile perform similarly well (see Supplementary S3).

2.2 Self-reported survey data versus mobility data

By considering self-reported survey data, we capture the sharp decline in the reproduction number after the lockdown’s announcement, i.e., about two weeks before its nationwide implementation (see Supplementary Table S1 for a detailed timeline). This early signal is not as pronounced in the combined mobility time series from Google and Apple that have been proposed in [26], nor in the telecommunication data from Danish mobile network operators (see Fig. 1 and Fig. 2 for a visual comparison on the national and regional level, respectively). In addition, we also observe a sharp increase in mobility shortly after the lockdown’s implementation, which does not correspond to the inferred reproduction number and thus does not translate into increased
2.3 Understanding the role of contact-types

Fig. 2  Regional-level comparison. 1st row: Hospitalizations. 2nd row: inferred reproduction number from regional hospitalizations with mean and 95% CI. 3rd-6th row: survey data (70th percentile threshold), Google mobility, Apple mobility, and telecommunication data (Telco). We mark the lockdown’s first announcement, it’s partial and national implementation with a solid vertical line, a dashed vertical line and shaded vertical area, respectively.

hospitalizations. This decoupling between mobility and disease dynamics has been previously observed for other countries [26, 33]. A quantitative model comparison with LOO cross-validation confirms that self-reported survey data gives the best out-of-sample predictions for hospitalizations (see Fig. 3).

We find a more nuanced result when comparing self-reported contacts to the individual data streams provided by Google (see Supplementary Note S6). In particular, the category “Retail & Recreation” performs only marginally worse suggesting that disease relevant contacts are highly context dependent - A result that we will examine in the following section.
3 Discussion

During a lockdown, decision-makers need high-fidelity, real-time information about social behavior in order to carefully calibrate restrictions to both the epidemic wave and levels of public compliance. Interventions that are too lenient...
will not sufficiently reduce the wave, while too severe interventions (e.g., curfews) may have significant negative externalities on, for example, public trust and mental health [4, 5].

To this end, researchers and authorities worldwide have relied on mobility data, which have been cheaply available as they were already unobtrusively collected by, for example, private tech companies. At the same time, such reliance entails a dependency on data collected by company actors and data which may raise privacy issues.

In the present analysis, we have provided evidence for the usefulness of daily surveys of nationally representative samples as an alternative source of
Fig. 5  Risk-taking behaviour towards friends and strangers are the single best predictors for the observed hospitalizations (see Supplementary Table S6 for details). We present the difference in LOO cross-validation w.r.t the best performing model and plot the mean and 95% CI as circles and vertical bars. In Supplementary Table S7, we show that the combination of risk-taking behaviour towards colleagues and family members performs similarly well.

information during a lockdown. While the use of surveys has been recommended during the COVID-19 pandemic by WHO [10] and on the basis of the SARS epidemic in Hong Kong [9], the present analysis provides one of the first attempts to quantify the predictive validity of surveys of self-reported behavior during a lockdown. In contrast, prior research has focused on the behavioral antecedents of behavior such as self-reported fear of COVID-19 [25]. While understanding the impact of such antecedents is a theoretically important endeavour, more direct measures of behavior may be preferable for a monitoring purpose (see also Supplementary Fig. S4 and Supplementary Table S3 for a comparison with indirect measures from our survey).

The analyses provides proof-of-concept that self-reported measures of behavior can be superior to mobility. Given the widespread use of mobility data it is relevant to ask why survey data fared better. Unlike the telco data and the combined timeseries from Google and Apple, respectively, the survey data was able to capture behavioural changes weeks before the lockdown’s implementation. Parts of the effect can be explained by partial lockdowns. However, we see similar decreases of activity also in regions that were not targeted with the partial lockdown and in addition, we observe an early increase in risk-awareness (see Supplementary Fig. S5). This observation hints at an additional indirect, i.e., psychological effect: Individuals adjust their behaviour in response to an increased perceived threat due to rising case numbers or intensified political discussions that culminated in the announced lockdown on 07-December-2020. This finding suggests that part of the problem of mobility data may be that it is too coarse and, hence, does not capture the micro-adjustments in social behavior that people make when they are concerned with infection risk such as standing further away from others in public queues, not mingling with co-workers at the workplace and so forth.

Moreover, mobility increases shortly after the lockdown’s implementation with little effect on hospitalizations. This decoupling between mobility and reproduction number has been previously observed in other countries...
Unlike mobility, self-reported contacts provide a more direct measure of behaviour and thus improves predictability months after the lockdown’s implementation.

At the same time, it is relevant to note that a more detailed analysis of the individual Google data streams revealed the importance of context-dependent contacts: Our analysis finds that “Retail & Recreation” performs only marginally worse than self-reported contacts and can be best explained by risk-taking behaviour towards strangers (see Supplementary Fig. S7).

Finally, we find that risk-taking behaviour towards strangers and friends provide the best predictors for hospitalizations, although, a joint model that includes contacts to colleagues and family members performs similarly well. This behaviour could be explained by their complementary dynamics during the Christmas period: Holidays implied less contacts to colleagues and larger gatherings with family members.

Our inability to predict the rise of COVID-19 related hospitalizations prior to the lockdown’s announcement suggests that there are multiple possibilities of improving the measures used for monitoring public behavior during an epidemic. When knowledge has been gathered about the main pathways of transmission, researchers and authorities can more directly ask questions about social interactions in situations that enhances or inhibits transmission risk. During the COVID-19 pandemic, for example, it would be relevant to know whether the contact occurred inside or outside, especially as temperatures drop and individuals adjust their behaviour. Moreover, we know now about the importance of transmission in children and young adults below 18, which could not be included in the study. We believe that the lack of contextual information and representativeness limits the usefulness of our data set to predict the onset of the second wave of COVID-19 infections. (see Supplementary Fig. S1).

In summary, the present analysis has provided proof-of-concept regarding the usefulness of survey data as public policy tool for monitoring compliance with the announcement and implementation of lockdowns. Even though, the analyses we present are narrowly focused on a single lockdown, they provide evidence in support for the WHO’s recommendation to integrate social science methods such as surveys into pandemic surveillance and management.

4 Materials and Methods

4.1 Data

We use survey data from the HOPE (‘How Democracies Cope With COVID-19’) research project (www.hope-project.dk). Specifically, the HOPE-project fielded daily nationally representative survey in Denmark starting from mid-May 2020. Kantar Gallup, a private company, conducts the data collection until the end of April 2022. Each day a nationally representative sample (with a daily target of 500 complete interviews) reports on their protective behaviour and perceptions of the COVID-19 pandemic. Participants are Danish citizens
4 MATERIALS AND METHODS

aged 18 years or older. They are recruited using stratified random sampling – on age, sex and geographical location – based on the database of Danish social security numbers. The mobility data comes from Apple [34], Google [35] and major Danish mobile phone network operators [36] (for full description, see Supplementary Sec. S4.2).

4.2 Model description

We observe regional COVID-19 related hospitalizations, which derive from an initial number of infected and the time-varying reproduction number. We parametrize the latter using behavioural survey data and mobility time series. Our approach is a variant of the semi-mechanistic hierarchical Bayesian model of Flaxman et al. [28] and Unwin et al. [27], with the key difference that we use daily COVID-19 related hospitalizations. In Denmark, hospitalizations are a reliable proxy for pandemic activity available. Unlike death counts, hospitalizations are recorded with a significantly smaller delay and give a better signal-to-noise ratio for regions with little epidemic activity. The number of positive PCR-cases, on the other hand, suffers from confounding through varying test intensity during the Christmas holidays and more importantly, we can rely on a well-studied infection-to-hospitalization delay distribution, which is less sensitive to country-specific testing protocols.

The code is written in the Julia programming language [37] using the Turing.jl package [38] for Bayesian inference. The source code is fully accessible on GitHub [39]. In the following, we provide the mathematical details of the epidemiological model.

Observation model: As observations, we take the daily number of hospitalizations \( H_{t,r} \) at time \( t \) in region \( r \) and assume these are drawn from a Negative Binomial distribution with mean \( h_{t,r} \) and over-dispersion factor \( \phi \):

\[
H_{t,r} \sim \text{NegBinom} \left( h_{t,r}, h_{t,r} + \frac{h_{t,r}^2}{\phi} \right) \tag{2}
\]

\[
\phi \sim \text{Gamma}(\text{mean} = 50, \text{std} = 20) \tag{3}
\]

From the expected number of hospitalizations \( h_{t,r} \), we derive the latent, i.e., unobserved number of new infections \( i_{t,r} \). Two factors link infections to hospitalizations: (a) The conditional probability \( \alpha \) of hospitalization following an infection and (b) the corresponding delay distribution \( \pi \):

\[
h_{t,r} = \alpha \sum_{\tau=0}^{t-1} i_{\tau,r} \pi_{t-\tau} \tag{4}
\]

\[
\alpha \sim \text{Normal}^+(0.028, 0.002) \tag{5}
\]

\[
\pi \sim \text{Gamma}(\text{mean} = 10, \text{std} = 20) \tag{6}
\]
4.2 Model description

We estimate the infection hospitalization rate $\alpha$ in Eq. 5 from a seroprevalence study [40]. The results are, however, not sensitive to this value as we don’t account for the depletion of susceptible. The delay $\pi$ is a sum of two independent random variables, i.e. the incubation period and the time from onset of infection to hospitalization [41]. We take the corresponding distributions from previous studies and parametrize the incubation period by a Gamma distribution with a mean of 5.1 days and a coefficient of variation of 0.86 [42] and the infection to hospitalization delay by a Weibull distribution with a mean of 5.506 days and a shape parameter 0.845 [41], which corresponds to a standard deviation of 8.4 days:

$$\pi \sim \text{Gamma}(\text{mean} = 5.1, \text{CV} = 0.86) + \text{Weibull}(\text{shape} = 0.845, \text{scale} = 5.506)$$

(7)

We then discretize the continuous distribution $\pi$ by $\pi_i = \int_{i-0.5}^{i+0.5} g(\tau) d\tau$ for $i = 2, 3, \ldots$ and $\pi_1 = \int_0^{1.5} g(\tau) d\tau$ for application in Eq. 4.

**Infection model:** The (unobserved) number of new infections, $i_{t,r}$, evolves according to a discrete renewal process. This approach has been widely used in epidemic modelling [28, 43–45], is related to the classical susceptible-infected model [46] and has a theoretical foundation in age-dependent branching processes [43, 47]. New infections in region $r$ at time $t$ are a product of the time-varying reproduction number $R_{t,r}$ and the number of individuals that are infectious at time $t$. The latter is a convolution of past infections and the generation interval $g_{\tau}$:

$$i_{t,r} = R_{t,r} \sum_{\tau=0}^{t-1} i_{\tau,r} g_{t-\tau}$$

(8)

The generation interval $g$ translates past infections to the present number of infectious individuals and following previous studies, we assume a Gamma distribution density $g(\tau)$ with mean 5.06 and SD 2.11 [48]:

$$g \sim \text{Gamma}(\text{mean} = 5.06, \text{SD} = 2.11)$$

(9)

Again, we discretize the continuous distribution by $g_i = \int_{i-0.5}^{i+0.5} g(\tau) d\tau$ for $i = 2, 3, \ldots$ and $g_1 = \int_0^{1.5} g(\tau) d\tau$ to be used in Eq. 8. The convolution in Equ. 8 requires a history of infectious individuals for initialization, which we estimate prior to the analysis (see Supplementary Note S1.1).

**Transmission model:** At the heart of the analysis is the instantaneous reproduction number $R_{t,r}$ for region $r$ at time $t$. It determines the number of secondary transmissions from the current number of infectious individuals. We implement a *parametric* and a *non-parametric* variant of the model akin to [26].
The non-parametric model implements a latent random-walk, i.e., an AR(1) process that allows to track daily changes of the reproduction number:

\[ R_{t,r} = R_{0,r} \exp(\rho_{t,r}) \]  
\[ \rho_{t,r} \sim \text{Normal}(\rho_{t-1,r}, \sigma) \]  
\[ \sigma \sim \text{Normal}^+(0.3, 0.02) \]  

Here, the latent variable \( \rho_{t,r} \) performs a random walk with a typical step size of \( \sigma \). Hence, the number of inferable parameters \( \rho_{t,r} \) equals the number of observation days for each region \( r \). The step size \( \sigma \) determines the smoothness of the resulting reproduction number and we choose the same prior distribution as in [27]. The non-parametric model allows us to infer the "ground truth" that we use for visual comparison.

The parametric model, on the other hand, takes a data stream \( X_{t,r} \) for every region \( r \) as a parametrization of the reproduction number:

\[ R_{t,r} = R_{0,r} \exp(e_r X_{t,r}) \]  
\[ e_r \sim \text{Normal}(e, s) \]  
\[ e \sim \text{SkewedLaplace}(\mu = 0, \sigma = 0.7, \alpha = 0.2) \]  
\[ s \sim \text{Gamma}(\text{mean} = 0.07, \text{SD} = 0.05) \]  

The predictors are normalized such that \( X_{t,r} \) gives the change in behaviour at time \( t \) relative to the first day, i.e. \( t_0 = 2020-12-01 \), in region \( r \). Thus, the effect size \( e_r \) in Eq. 14 translate a relative change in the predictor \( X_{t,r} \) to a change in the regional reproduction number \( R_{t,r} \). We pool information in order to reduce regional biases and to give a robust country-level effect estimate \( e \) akin to multi-level models [29].

With more contacts or a higher mobility level, we expect an increased disease transmissibility and therefore, we choose a skewed Laplace distribution as a prior for the pooled effect parameter \( \mu_e \) [49]. Furthermore, we choose a shrinking prior on the dispersion parameter \( s \) to limit regional differences and thus reduce potential overfitting given the limited data. Note, however, that substantial effect differences are still inferrable if the data provides sufficient evidence.

5 Data availability

All data necessary for the replication of our results is collated in https://github.com/andreaskoher/Covid19Survey. The hospitalization data originated from Statens Serum Institute https://covid19.ssi.dk/.
6 Code availability

All code necessary for the replication of our results is collated in https://github.com/andreaskoher/Covid19Survey

7 Author contributions

AK, FJ, MBP, and SL conceived the study and wrote the text. AK carried out modeling and analyses. FJ and MBP collected the survey data.

8 Competing interests

The authors declare no competing interests.

References

[1] Soltesz, K., Gustafsson, F., Timpka, T., Jaldén, J., Jidling, C., Heimerson, A., Schön, T.B., Spreco, A., Ekberg, J., Dahlström, Ö., et al.: The effect of interventions on covid-19. Nature 588(7839), 26–28 (2020)

[2] Brauner, J.M., Mindermann, S., Sharma, M., Johnston, D., Salvatier, J., Gavenciak, T., Stephenson, A.B., Leech, G., Altman, G., Mikulik, V., et al.: Inferring the effectiveness of government interventions against covid-19. Science 371(6531), 9338 (2021)

[3] Banks, J., Xu, X.: The mental health effects of the first two months of lockdown during the covid-19 pandemic in the uk. Fiscal Studies 41(3), 685–708 (2020)

[4] Jørgensen, F., Bor, A., Rasmussen, M.S., Lindholt, M.F., Petersen, M.B.: Pandemic fatigue fueled political discontent during the covid-19 pandemic. Proceedings of the National Academy of Sciences 119(48), 2201266119 (2022)

[5] Clemmensen, C., Petersen, M.B., Sørensen, T.I.: Will the covid-19 pandemic worsen the obesity epidemic? Nature Reviews Endocrinology 16(9), 469–470 (2020)

[6] Fernandez-Cassi, X., Scheidegger, A., Bänziger, C., Cariti, F., Corzon, A.T., Ganesanandamoorthy, P., Lemaitre, J.C., Ort, C., Julian, T.R., Kohn, T.: Wastewater monitoring outperforms case numbers as a tool to track covid-19 incidence dynamics when test positivity rates are high. Water research 200, 117252 (2021)

[7] Kogan, N.E., Clemente, L., Liautaud, P., Kaashoek, J., Link, N.B., Nguyen, A.T., Lu, F.S., Huybers, P., Resch, B., Havas, C., et al.: An
early warning approach to monitor covid-19 activity with multiple digital traces in near real time. Science Advances 7(10), 6989 (2021)

[8] Benita, F.: Human mobility behavior in covid-19: A systematic literature review and bibliometric analysis. Sustainable Cities and Society 70, 102916 (2021)

[9] Leung, G.M., Ho, L.-M., Chan, S.K., Ho, S.-Y., Bacon-Shone, J., Choy, R.Y., Hedley, A.J., Lam, T.-H., Fielding, R.: Longitudinal assessment of community psychobehavioral responses during and after the 2003 outbreak of severe acute respiratory syndrome in hong kong. Clinical Infectious Diseases 40(12), 1713–1720 (2005)

[10] Organization, W.H., et al.: Survey tool and guidance: rapid, simple, flexible behavioural insights on covid-19: 29 july 2020. Technical report (2020)

[11] Bonney, R., Shirk, J.L., Phillips, T.B., Wiggins, A., Ballard, H.L., Miller-Rushing, A.J., Parrish, J.K.: Next steps for citizen science. Science 343(6178), 1436–1437 (2014)

[12] Buckee, C.O., Balsari, S., Chan, J., Crosas, M., Dominici, F., Gasser, U., Grad, Y.H., Grenfell, B., Halloran, M.E., Kraemer, M.U., et al.: Aggregated mobility data could help fight covid-19. Science 368(6487), 145–146 (2020)

[13] Alessandretti, L.: What human mobility data tell us about covid-19 spread. Nature Reviews Physics 4(1), 12–13 (2022)

[14] Rüdiger, S., Konigorski, S., Rakowski, A., Edelman, J.A., Zernick, D., Thieme, A., Lippert, C.: Predicting the sars-cov-2 effective reproduction number using bulk contact data from mobile phones. Proceedings of the National Academy of Sciences 118(31), 2026731118 (2021) https://www.pnas.org/doi/pdf/10.1073/pnas.2026731118. https://doi.org/10.1073/pnas.2026731118

[15] Aktay, A., Bavadekar, S., Cossoul, G., Davis, J., Desfontaines, D., Fabricant, A., Gabrilovich, E., Gadepalli, K., Gipson, B., Guevara, M., et al.: Google covid-19 community mobility reports: anonymization process description (version 1.1). arXiv preprint arXiv:2004.04145 (2020)

[16] Hu, T., Wang, S., She, B., Zhang, M., Huang, X., Cui, Y., Khuri, J., Hu, Y., Fu, X., Wang, X., et al.: Human mobility data in the covid-19 pandemic: characteristics, applications, and challenges. International Journal of Digital Earth 14(9), 1126–1147 (2021)

[17] Jung, G., Lee, H., Kim, A., Lee, U.: Too much information: assessing
privacy risks of contact trace data disclosure on people with covid-19 in south korea. Frontiers in public health 8, 305 (2020)

[18] Bollyky, T.J., Hulland, E.N., Barber, R.M., Collins, J.K., Kiernan, S., Moses, M., Pigott, D.M., Reiner Jr, R.C., Sorensen, R.J., Abbafati, C., et al.: Pandemic preparedness and covid-19: an exploratory analysis of infection and fatality rates, and contextual factors associated with preparedness in 177 countries, from jan 1, 2020, to sept 30, 2021. The Lancet (2022)

[19] Krosnick, J.A.: Survey research. Annual review of psychology 50(1), 537–567 (1999)

[20] Schuman, H., Presser, S.: Questions and Answers in Attitude Surveys: Experiments on Question Form, Wording, and Context. Sage, ??? (1996)

[21] Larsen, M., Nyrup, J., Petersen, M.B.: Do survey estimates of the public’s compliance with covid-19 regulations suffer from social desirability bias? Journal of Behavioral Public Administration 3(2) (2020)

[22] Hansen, P.G., Larsen, E.G., Gundersen, C.D.: Reporting on one’s behavior: a survey experiment on the nonvalidity of self-reported covid-19 hygiene-relevant routine behaviors. Behavioural Public Policy, 1–18 (2021)

[23] Gollwitzer, A., McLoughlin, K., Martel, C., Marshall, J., Höhs, J.M., Bargh, J.A.: Linking self-reported social distancing to real-world behavior during the covid-19 pandemic. Social Psychological and Personality Science 13(2), 656–668 (2022) https://doi.org/10.1177/19485506211018132. https://doi.org/10.1177/19485506211018132

[24] Kalleitner, F., Schiestl, D.W., Heiler, G.: Varieties of mobility measures: Comparing survey and mobile phone data during the COVID-19 pandemic. preprint (2021). https://doi.org/10.31235/osf.io/r78fk

[25] Jirsa, V., Petkoski, S., Wang, H., Woodman, M., Fousek, J., Betsch, C., Felgendreuff, L., Böhm, R., Lilleholt, L., Zettler, I., et al.: Integrating psychosocial variables and societal diversity in epidemic models for predicting covid-19 transmission dynamics. medRxiv (2020)

[26] Nouvellet, P., Bhatia, S., Cori, A., Ainslie, K.E., Baguelin, M., Bhatt, S., Boonyasiri, A., Brazseau, N.F., Cattarino, L., Cooper, L.V., et al.: Reduction in mobility and covid-19 transmission. Nature communications 12(1), 1–9 (2021)

[27] Unwin, H.J.T., Mishra, S., Bradley, V.C., Gandy, A., Mellan, T.A., Coupland, H., Ish-Horowicz, J., Vollmer, M.A., Whittaker, C., Filippi,
S.L., *et al.*: State-level tracking of covid-19 in the united states. *Nature communications* **11**(1), 1–9 (2020)

[28] Flaxman, S., Mishra, S., Gandy, A., Unwin, H.J.T., Mellan, T.A., Coupland, H., Whittaker, C., Zhu, H., Berah, T., Eaton, J.W., *et al.*: Estimating the effects of non-pharmaceutical interventions on covid-19 in europe. *Nature* **584**(7820), 257–261 (2020)

[29] Gelman, A., Carlin, J.B., Stern, H.S., Rubin, D.B.: Bayesian Data Analysis. Chapman and Hall/CRC, ??? (1995)

[30] Vehtari, A., Gelman, A., Gabry, J.: Practical bayesian model evaluation using leave-one-out cross-validation and waic. *Statistics and Computing* (2016). https://doi.org/10.1007/s11222-016-9696-4

[31] Jørgensen, F., Lindholt, M.F., Bor, A., Petersen, M.B.: Does face mask use elicit risk-compensation? quasi-experimental evidence from denmark during the sars-cov-2 pandemic. *European Journal of Public Health* (2020)

[32] Sneppen, K., Nielsen, B., Taylor, R., Simonsen, L.: Overdispersion in covid-19 increases the effectiveness of limiting nonrepetitive contacts for transmission control. *Proceedings of the National Academy of Sciences* **118**, 2016623118 (2021). https://doi.org/10.1073/pnas.2016623118

[33] Schlosser, F., Maier, B.F., Jack, O., Hinrichs, D., Zachariae, A., Brockmann, D.: Covid-19 lockdown induces disease-mitigating structural changes in mobility networks. *Proceedings of the National Academy of Sciences* **117**(52), 32883–32890 (2020) https://www.pnas.org/doi/pdf/10.1073/pnas.2012326117. https://doi.org/10.1073/pnas.2012326117

[34] Apple. Mobility Trends. https://www.apple.com/covid19/mobility. Accessed: 2022-03-31

[35] Google. Community mobility reports. https://www.google.com/covid19/mobility/index.html?hl=en. Accessed: 2022-03-31

[36] Edsberg Mølgaard, P., Lehmann, S., Alessandretti, L.: Understanding components of mobility during the covid-19 pandemic. *Philosophical Transactions of the Royal Society A* **380**(2214), 20210118 (2022)

[37] Bezanson, J., Edelman, A., Karpinski, S., Shah, V.B.: Julia: A fresh approach to numerical computing. *SIAM review* **59**(1), 65–98 (2017)

[38] Ge, H., Xu, K., Ghahramani, Z.: Turing: a language for flexible probabilistic inference. In: *International Conference on Artificial
Intelligence and Statistics, AISTATS 2018, 9-11 April 2018, Playa Blanca, Lanzarote, Canary Islands, Spain, pp. 1682–1690 (2018). http://proceedings.mlr.press/v84/ge18b.html

[39] publicly available source code. https://github.com/andreaskoher/Covid19Survey. Accessed: 2022-05-21

[40] Erikstrup, C., Hother, C.E., Pedersen, O.B.V., Mølbak, K., Skov, R.L., Holm, D.K., Sækmose, S.G., Nilsson, A.C., Brooks, P.T., Boldsen, J.K., Mikkelsen, C., Gybel-Brask, M., Sørensen, E., Dinh, K.M., Mikkelsen, S., Møller, B.K., Haunstrup, T., Harritsshøj, L., Jensen, B.A., Hjalgrim, H., Lillevang, S.T., Ullum, H.: Estimation of SARS-CoV-2 Infection Fatality Rate by Real-time Antibody Screening of Blood Donors. Clinical Infectious Diseases 72(2), 249–253 (2020). https://doi.org/10.1093/cid/ciaa849

[41] Faes, C., Abrams, S., Van Beckhoven, D., Meyfroidt, G., Vlieghe, E., Hens, N., on COVID-19 Hospital Surveillance, B.C.G.: Time between symptom onset, hospitalisation and recovery or death: Statistical analysis of belgian covid-19 patients. International Journal of Environmental Research and Public Health 17(20) (2020). https://doi.org/10.3390/ijerph17207560

[42] Lauer, S., Grantz, K., Bi, Q., Jones, F., Zheng, Q., Meredith, H., Azman, A., Reich, N., Lessler, J.: The incubation period of coronavirus disease 2019 (covid-19) from publicly reported confirmed cases: Estimation and application. Annals of internal medicine 172 (2020). https://doi.org/10.7326/M20-0504

[43] Bhatt, S., Ferguson, N., Flaxman, S., Gandy, A., Mishra, S., Scott, J.A.: Semi-mechanistic bayesian modeling of covid-19 with renewal processes. arXiv preprint arXiv:2012.00394 (2020)

[44] Cori, A., Ferguson, N.M., Fraser, C., Cauchemez, S.: A New Framework and Software to Estimate Time-Varying Reproduction Numbers During Epidemics. American Journal of Epidemiology 178(9), 1505–1512 (2013) https://academic.oup.com/aje/article-pdf/178/9/1505/17341195/kwt133.pdf. https://doi.org/10.1093/aje/kwt133

[45] Nouvellet, P., Cori, A., Garske, T., Blake, I.M., Dorigatti, I., Hinsley, W., Jombart, T., Mills, H.L., Nedjati-Gilani, G., Van Kerkhove, M.D., Fraser, C., Donnelly, C.A., Ferguson, N.M., Riley, S.: A simple approach to measure transmissibility and forecast incidence. Epidemics 22, 29–35 (2018). https://doi.org/10.1016/j.epidem.2017.02.012. The RAPIDD Ebola Forecasting Challenge

[46] Kermack, W.O., McKendrick, A.G.: A contribution to the mathematical
theory of epidemics. Proceedings of the royal society of london. Series A, Containing papers of a mathematical and physical character **115**(772), 700–721 (1927)

[47] Mishra, S., Berah, T., Mellan, T.A., Unwin, H.J.T., Vollmer, M.A., Parag, K.V., Gandy, A., Flaxman, S., Bhatt, S.: On the derivation of the renewal equation from an age-dependent branching process: an epidemic modelling perspective. arXiv preprint arXiv:2006.16487 (2020)

[48] Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., Parker, M., Bonsall, D., Fraser, C.: Quantifying sars-cov-2 transmission suggests epidemic control with digital contact tracing. Science **368**(6491), 6936 (2020) https://www.science.org/doi/pdf/10.1126/science.abb6936. https://doi.org/10.1126/science.abb6936

[49] Zhu, D., Zinde-Walsh, V.: Properties and estimation of asymmetric exponential power distribution. Journal of Econometrics **148**(1), 86–99 (2009). https://doi.org/10.1016/j.jeconom.2008.09.038

[50] Hoffman, M.D., Gelman, A., *et al.*: The no-u-turn sampler: adaptively setting path lengths in hamiltonian monte carlo. J. Mach. Learn. Res. **15**(1), 1593–1623 (2014)

[51] Adam, D.C., Wu, P., Wong, J.Y., Lau, E.H., Tsang, T.K., Cauchemez, S., Leung, G.M., Cowling, B.J.: Clustering and superspreading potential of sars-cov-2 infections in hong kong. Nature Medicine **26**(11), 1714–1719 (2020)

[52] Telco mobility data. https://covid19.compute.dtu.dk/visualizations/telco_brush/. Accessed: 2022-03-31
S1 Extended information on the epidemic model

S1.1 Initialization of the epidemic model

We use two different models for inference that we refer to as the *non-parametric* and the *parametric* model. Both models require a history of latent infections $i_{t,r}$ for $t \leq 0$ and an effective reproduction number $R_{0,r}$ for every region $r$.

**The non-parametric model:** Observations start on 01-August-2020, i.e., well before the second wave of Covid infections (see Fig. S1). Therefore, we can reasonably assume that the number of latent infections is constant, i.e., $i_{t,r} \equiv i_{0,r}$, in order to initialize the discrete renewal process for $t > 0$. We infer $i_{0,r}$ from the number of PCR-positive cases $I_{0,r}$ on 01-August-2020 and roughly assume an underestimation factor of three:

$$i_{0,r} \sim \text{Exponential}(3I_{0,r})$$  
(1)

The exponential prior implies a broad uncertainty and thus sufficient flexibility of the inference model. Note that we choose PCR-positive cases to initialize the number of infected because hospitalizations were very low and noisy at the start of the second wave, making incidence data in this case a stronger choice for initializing the model. Moreover, we choose the initial reproduction number to be around one, which reflects our prior believe that the epidemic was under control well before the second wave of infections:

$$R_{0,r} \sim \text{Normal}^+(1.0, 0.1)$$  
(2)

**The parametric model:** Observations start on 01-December-2020, i.e., about one week prior to the lockdown’s announcement and well within the second wave of Covid-19 infections. Here, the assumption of constant $i_{t,r} \equiv i_{0,r}$ for $t \leq 0$ is not suitable as well as $R_{0,r} \approx 1$. Instead, we take posterior samples from the non-parametric model, marked with an asterisk, for initialization: In particular, we take the mean over the posterior samples of the latent infections $\langle i \rangle^*_{t,r}$ and scale the timeseries with a factor $\nu$ that corresponds roughly to the posterior uncertainty of $i^*_{t,r}$. Hence, we obtain the initial number of latent
infections according to:

\[ \nu \sim \text{Normal}^+(1, 0.1) \]  

\[ i_{t,r} = \nu \cdot \langle i \rangle_{t,r} \text{ for all } t \leq 0 \]  

Similarly, we initialize the effective reproduction number \( R_{0,r} \) by fitting a Normal distribution to the posterior samples \( R^*_{0,r} \) from the non-parametric model at the initial observation, i.e. 01-December-2020:

\[ R_{0,r} \sim \text{Normal}^+(\mu_R, \sigma_R) \]  

\[ \mu_R = \text{mean}(R^*_{0,r}) \]  

\[ \sigma_R = \text{std}(R^*_{0,r}) \]  

### S1.2 Joint model with multiple predictors

For the parametric model with multiple predictors \( c \), we modify Eq. S1.2 according to:

\[ R_{t,r} = R_{0,r} \exp \left( \sum_c e^c_r X^c_{t,r} \right) \]  

\[ e^c_r \sim \text{Normal}(e^c, s) \]  

\[ e^c \sim \text{SkewedLaplace}(\mu = 0, \sigma = 0.7, \alpha = 0.2) \]  

\[ s \sim \text{Gamma}(\text{mean} = 0.07, \text{SD} = 0.05) \]

The reproduction number in region \( r \) at time \( t \) is a linear combination multiple data streams \( X^c_{t,r} \), with an exponential link-function to ensure positivity. Each predictor is normalized such that \( X^c_{t,r} \) gives the change in behaviour or mobility at time \( t \) relative to the first day, i.e. 2020-12-01, in region \( r \). Thus, the effect sizes \( e^c_r \) translate a relative change \( X^c_{t,r} \) in the predictor to a change in the reproduction number \( R_{t,r} \). We pool effect sizes \( e^c_r \) to reduce regional biases and obtain a national-level effect size \( e^c \) for each predictor \( c \).
S2 MCMC sampling

We implement the epidemiological model in the Julia programming language [37] using the Turing.jl package [38] for Bayesian inference. In particular, we use the No-U-Turn sampler [50], i.e. a variant of the Hamilton Monte-Carlo sampler with a target acceptance rate of 0.99 and a maximum tree-depth of 8. We draw 5000 samples from 5 chains each and discard the first 1000 for warm-up.

All inference results report no divergent transitions. Also, the maximum Gelman–Rubin diagnostic and $\hat{R}$ statistics is below 1.1 for all simulations, thus indicating sufficient mixing and convergence of the Monte-Carlo chains.

Further implementation details and a step-by-step tutorial to reproduce the main results are available on GitHub [39].
S3 Covid-19 restrictions timeline

| date      | action                                                                                                                                 |
|-----------|----------------------------------------------------------------------------------------------------------------------------------------|
| 2020-12-07 | partial lockdown announced*: significant tightening of Covid-19 restrictions in 38 municipalities across Denmark, including the country’s three largest cities, Copenhagen, Aarhus, and Odense. |
| 2020-12-09 | partial lockdown in effect                                                                                                                                                                   |
| 2020-12-16 | full lockdown announced**. Nation-wide Restrictions are gradually increased, starting from 2020-12-17 until the full lockdown on 2020-12-25 |
| 2020-12-17 | shopping malls closed                                                                                                                                                                         |
| 2020-12-21 | school closure & shut down of businesses involving close contact such as                                                                                                                                 |
| 2020-12-24 | private events over Christmas are encouraged not to exceed 10 people                                                                                                                                 |
| 2020-12-25 | all non-essential retail businesses closed / "full lockdown"                                                                                                                                 |

Table S1: The above timeline of Denmark’s second Covid-19 lockdown follows online media announcements:

* [https://www.thelocal.dk/20201207/latest-denmark-announces-partial-covid-19-lockdown-until-2021/](https://www.thelocal.dk/20201207/latest-denmark-announces-partial-covid-19-lockdown-until-2021/), accessed: 2022-04-20

** [https://www.thelocal.dk/20201216/new-denmark-announces-national-lockdown-from-christmas-day/](https://www.thelocal.dk/20201216/new-denmark-announces-national-lockdown-from-christmas-day/), accessed: 2022-04-20.
S4 Extended data discussion

S4.1 Survey data

We contact participants via eBoks, the official electronic mail system of public authorities, and provide no financial incentives. Notably, about 8% of the Danish population, mainly older people, are exempted from eBoks. Despite this limitation and a response rate of 25%, the participants are representative of the broad Danish population regarding the stratified characteristics [31]. Further details on sampling and questions are available in [31].

From our survey, we select the self-reported number of contacts within a two-meter distance for at least 15 minutes and differentiate between contacts to family members, friends, colleagues and strangers, where the latter refers to all remaining contact types. Our analysis focuses on the period from 2020-12-01 to 2021-02-01 with 15,595 participants split into the five regions of Denmark: Region Hovedstaden (Capital), Region Midtjylland (Center), Region Nordjylland (North), Region Sjælland (Zealand), Region Syddanmark (South). We remove unreasonable outliers that include negative numbers and values above 50, 100, 100 and 1000 for contacts to family members, friends, colleagues and strangers, respectively, thus dropping 0.3% of all responses. By summing up the reported number of context-dependent contacts, we obtain every survey participant’s total number of contacts. Next, we mark a participant as risk-taking, either context-depending or in terms of total contacts, and derive the daily fraction of risk-takers. This quantity is robust to outliers and reflects our understanding that super-spreading events drive Covid-19 infections [51]. Finally, we take a 7-day moving average, centered on day four and calculate the change in behaviour relative to the first observation day, i.e., 2020-12-01. We thus have five data streams for each of the five regions of Denmark: risk-taking behaviour given overall contacts and four context-depending time series (see Fig. 1 panel B and appendix Fig. S8), respectively.

S4.2 Mobility data

Apple provides three data streams, namely, driving, walking, and transit. The latter is not available in all regions of Denmark, and therefore we exclude it from the analysis.

The Google data includes six time-series: grocery & pharmacy, retail & recreation, transit stations, workplaces, parks, and residential. We exclude parks because data is too sparse on a regional level. In addition to the individual data streams, we combine driving and walking to a single Apple time series, and equally for Google, we use grocery & pharmacy, retail & recreation, transit stations, and workplaces as suggested in [26].

The telecommunication (telco) time series derives from aggregated mobility flows within and between municipalities. Denmark’s leading mobile network operators provided the data to the Statens Serum Institut (SSI), covering 2020-02-01 to 2021-06-30. The SSI officially requested the data to improve national
Covid-19 models and understand population behaviour in response to non-pharmaceutical interventions. Detailed information on the data is available in [36] and the complete data set can be downloaded from [52].

As a final preprocessing step to the mobility data from Apple, Google and the telco companies, we take a 7-days moving average and calculate the change in mobility relative to the first observation day on 01-December-2020.
Fig. S1 top panel: national hospitalizations from 2020-08-01 to 2021-02-20. We highlight the analysis window from 2020-12-01 to 2021-02-01, which is the focus of our paper, the lockdown’s announcement, its partial and nation-wide implementation. 2nd panel: inferred reproduction number $R_t$ from national hospitalizations. 3rd panel: fraction of Denmark’s vaccinated population. 4th panel: average daily temperature in Denmark. 5th panel: Risk-taking behaviour with a threshold at the 70th percentile. 6th panel: Aggregated mobility data from Google, Apple and telecommunication providers (Telco). The visual comparison between reproduction number and predictors, including our survey and mobility, demonstrates the limitations: All predictors decrease significantly in correspondence to the lockdown, however, neither mobility nor our survey correlate well with the reproduction number during the early phase. There are potentially many limiting factors, including vaccination campaigns (3rd panel), changing masking efforts, and seasonal effects (4th panel). To improve future surveys and potentially predict the onset of the second wave, it would be relevant to know whether contacts occurred inside or outside, especially as temperatures drop and individuals adjust their behaviour.
Fig. S2  Histogram over the reported contacts from 2020-08-01 to 2020-12-01. Left column: linear scaling with normalization to probabilities. Right column: Log scale without normalization, i.e. bins represent the number of survey participants that reported the corresponding number of close contacts. The linear scaling highlights the large fraction of individuals that report zero close contacts in the past 24h, whereas the log-scaling demonstrates the broad distribution of contacts, even after removing outliers as described in Sec. 4.1. We use these statistics to define risk-taking behaviour in the main text as follows: Given a threshold in terms of a percentile, we derive the corresponding number of contacts from the above distributions. Then, we mark individuals as risk-taking (towards the total number of contacts or context-dependent) if they report more than the threshold number of contacts and report the daily fraction of risk-taking individuals. The resulting time-series captures subtle behavioural changes in the population and is robust with respect to outliers.
S5  Extended information on risk-taking behaviour

Fig. S3  Comparison between $R_t$ and risk-taking behaviour. Top panel: reproduction number $R_t$, derived from national hospitalizations. Lower panel: changes in risk-taking behaviour given the total number of contacts and different thresholds in terms of percentiles (see Sec. 4.1 for details). Similar to Fig. 1 in the main text, but includes more thresholds. Risk-taking behaviour that is derived from a larger threshold, shows an increased response to the lockdown’s announcement and a smaller Christmas-related peak. Visually, this dynamics corresponds well to $R_t$ and we confirm the improved predictive performance quantitatively in Table S2 using the PSIS-LOO score.
Table S2 Predictive performance for different definitions of risk-taking behaviour. In detail, we compare thresholds that define risk-taking behaviour given the total number of contacts. As a threshold, we use the percentile of all reported contacts before the lockdown’s announcement, i.e. from 2020-08-01 to 2020-12-01 (see first panel in Fig. S2), and provide the corresponding number of contacts in a separate column. We calculate the PSIS-LOO score [30], which approximates the out-of-sample predictive performance and rank the results from highest to lowest performing. We consider the score difference significant if it is larger than the 95% CI (approx. twice the standard error) and highlight rows with bold letters that show a non-significant performance difference to the best performing model. Here, the 60th percentile performs best but, all thresholds above the 55th percentile are only insignificantly worse.

| rank | contacts | percentile | score difference | score difference (std) |
|------|----------|------------|-------------------|------------------------|
| 0    | > 6      | 60th       | -0.0              | 0.0                    |
| 1    | > 9      | 70th       | -0.696663         | 2.36629                |
| 2    | > 7      | 65th       | -2.1874           | 1.5744                 |
| 3    | > 11     | 75th       | -2.92527          | 3.75475                |
| 4    | > 18     | 85th       | -4.25635          | 5.00422                |
| 5    | > 14     | 80th       | -4.97029          | 5.52294                |
| 6    | > 5      | 55th       | -5.98605          | 2.38119                |
| 7    | > 24     | 90th       | -11.7012          | 6.85762                |
| 8    | > 4      | 50th       | -13.6783          | 4.1538                 |
| 9    | > 2      | 40th       | -16.0057          | 3.7325                 |
| 10   | > 3      | 45th       | -21.8684          | 4.5585                 |
| 11   | > 1      | 30th       | -22.1058          | 4.41053                |
| 12   | > 0      | 20th       | -28.049           | 5.57477                |

Table S3 Predictive performance for risk-taking behaviour and additional behavioural time-series from our survey. In detail, we compare risk-taking behaviour given the total number of contacts and a threshold at the 70th percentile against the mean response to additional survey questions. The latter are presented in Fig. S4 with details about the questions in the corresponding caption. We calculate the PSIS-LOO score, which approximates the out-of-sample predictive performance and rank the results from highest to lowest performing. We consider the score difference significant if it is larger than the 95% CI (approx. twice the standard error) and highlight rows with bold letters that show a non-significant performance difference. The PSIS-LOO score demonstrates that risk-taking behaviour outperforms indirect measures of behaviour from our questionnaire responses. In addition, this result confirms that our the survey captures early behavioural changes in different aspects of daily life with impact on disease transmission.

| rank | predictor                  | score difference | score difference (std) |
|------|----------------------------|-------------------|------------------------|
| 0    | risk-taking behaviour      | -0.0              | 0.0                    |
| 1    | avoid contact activities   | -9.21759          | 3.53417                |
| 2    | avoid crowded places       | -19.835           | 6.09498                |
| 3    | avoid contacts             | -33.1312          | 6.88432                |
| 4    | social distancing          | -47.014           | 8.52191                |
| 5    | threat to society          | -122.325          | 11.8105                |
Fig. S4  Comparison between national-level $R_t$ and additional behavioural time-series from the HOPE survey in the upper and lower panel, respectively. The latter represent changes in the mean response to a number of additional survey questions. The dynamics reflects a similar, though inverted, patterns to $R_t$ and risk-taking behaviour (see Fig. S3). Therefore, these time-series support our argument that our survey captures early behavioural changes around the lockdown’s announcement. The details: Participants responded on a 1-to-7 scale from "not at all" / "completely disagree" to "to a high degree" / "completely agree". The labels in the second panel correspond to the following questions / statements from the survey: (1) The Corona virus is a threat to Danish society. (2) To what extent did you yesterday avoid contacts? (3) To what extent did you yesterday keep 1-2 meters distance to other people? (4) To what extent did you yesterday avoid going to crowded places? (5) To what extent did you yesterday minimize activities where you have contact to other people?
We took a seven-day moving average of the mean response value. Table S3 evaluates the predictive performance of the above time-series in terms of PSIS-LOO scores.
Perceived threat of a Covid-19 infection may lead to behaviour change. 1st panel: $R_t$ derived from national-level hospitalizations. 2nd panel: mean response to the statement: *The Corona virus is a threat to Danish society.* 3rd panel: risk-taking behaviour with a threshold at the 70th percentile. The visual comparison suggests that the perceived threat the Covid pandemic leads to a behavioural change as measured by *risk-taking behaviour*.
S6 Extended comparison with mobility data

| rank | predictor       | score difference | score difference (std) |
|------|----------------|------------------|------------------------|
| 0    | survey         | -0.0             | 0.0                    |
| 1    | google         | -23.3503         | 7.98878                |
| 2    | telco          | -69.3159         | 11.3415                |
| 3    | apple          | -116.649         | 13.3013                |

Table S4 Self-reported survey data (Survey) demonstrates highest predictive performance compared to Google mobility, Apple mobility and telecommunication data (Telco). The details: Survey data refers to risk-taking behaviour on the total number of contacts with a threshold at the 70th percentile. We calculate the PSIS-LOO score, which approximates the out-of-sample predictive performance and rank the results from highest to lowest performing. We consider the score difference significant if it is larger than the 95% CI (approx. twice the standard error) and highlight rows with bold letters that show a non-significant performance difference. See Fig. 1 and S6 for a visual comparison of the time-series data.

| rank | predictor                           | score difference | score difference (std) |
|------|-------------------------------------|------------------|------------------------|
| 0    | Survey                             | -4.14564         | 4.92608                |
| 1    | Google (retail & recreation)       | -15.8254         | 7.32822                |
| 2    | Google (grocery & pharmacy)        | -23.2743         | 7.95421                |
| 3    | Google (transit stations)          | -23.4502         | 7.42688                |
| 4    | Apple (driving)                    | -92.5306         | 12.6706                |
| 5    | Apple (walking)                    | -116.769         | 13.3046                |
| 6    | Google (workplaces)                | -130.899         | 13.1453                |
| 7    | Google (retail & recreation)       | -138.908         | 13.4934                |

Table S5 Self-reported survey data (Survey) demonstrates highest predictive performance compared to individual data streams from Google and Apple mobility, though, the performance difference to Google’s retail & recreation is non-significant. The details: Survey data refers to risk-taking behaviour on the total number of contacts with a threshold at the 70th percentile. We calculate the PSIS-LOO score, which approximates the out-of-sample predictive performance and rank the results from highest to lowest performing. We consider the score difference significant if it is larger than the 95% CI (approx. twice the standard error) and highlight rows with bold letters that show a non-significant performance difference to the best performing model. See Fig. S6 for a visual comparison of the time-series data. Interestingly, the score difference to Google’s retail & recreation is non-significant. This observation appears plausible given (a) the increased risk for super-spreading events in retail and recreation spaces and (b) our results on risk-taking behaviour in different social contexts: Risk-taking behaviour towards friends and strangers predict hospitalizations best (Table S6) and the latter correlates well with Google’s retail & recreation (see Fig. S7).
Fig. S6  National-level comparison between $R_t$ and individual data streams from Google and Apple. 1st row: inferred reproduction number from national hospitalizations. 2nd row: Individual data streams from Google mobility trends [35]. We excluded the time-series "parks" because of too many missing values on the regional level. The combined time-series Google [26] includes transit station, workplaces, retail & recreation, grocery & pharmacy. 3rd row: Individual data streams from Apple mobility trends [34]. We exclude transit because of too many missing values on the regional level. The combined time series Apple [26] both remaining data streams. The comparison reveals that individual data streams from Google vary substantially whereas driving and walking from Apple show a similar dynamics. In Table S5, we compare the predictive performance of individual mobility data streams with risk-taking behaviour from our survey (3rd row).
Risk-taking behaviour towards strangers explains most of the variation in Google’s retail & recreation data stream. The details: We fit a linear model with retail & recreation as response variable $y_t$ at time $t$ and risk-taking behaviour as covariate $X^c_t$, where $c$ refers to family, colleagues, friends, or strangers, respectively:

$$y_t \sim \text{Normal}(\bar{y}_t, s)$$

$$\bar{y}_t = \sum_c e_c X^c_t$$

$$e_c \sim \text{Normal}(0, 1)$$

$$s = \text{Gamma}(\text{mean} = 5, \text{SD} = 3)$$

We use uninformative prior for the effect sizes $e_c$ and the observation noise $s$. The left panel shows posterior effect sizes with a circle and bar indicating mean and 95% CI, respectively. The right panel compares the response variable $y_t$ against the generated quantity $\bar{y}_t$ for a visual comparison of the fitting accuracy. We find that contacts to strangers is the dominant predictor for retail & recreation and the resulting fit appears in good agreement with the latter.
S7  Extended comparison between contact types

**Fig. S8**  Visual national-level comparison between $R_t$ and context-depending risk-taking behaviour. 1st row: Reproduction number $R_t$ inferred from national hospitalizations. 2nd column: risk-taking behaviour towards friends, strangers, and colleagues with a threshold at the 70th percentile. 3rd row: risk-taking behaviour towards family members.
Table S6  Risk-taking behaviour towards friends and strangers predict the observed hospitalizations best and colleagues performs only marginally worse. In detail, we define risk-taking behaviour with a threshold at the 70th percentile, calculate the PSIS-LOO score, which approximates the out-of-sample predictive performance, and rank the results from highest to lowest performing. We consider the score difference significant if it is larger than the 95% CI (approx. twice the standard error) and highlight rows with bold letters that show a non-significant performance difference to the best performing model. Here, risk-taking behaviour towards colleagues and family members outside the household perform significantly worse. However, this observation does not imply that the respective contacts are irrelevant for disease transmission. A joint model that includes all four predictors reveals that contacts to colleagues and family members have highly correlated effect sizes (see Fig. S9), suggesting that a combination of both data streams. Indeed, we find that risk-taking behaviour towards colleagues and family members together have a similar predictive performance to the best model (see Fig. S7).

Table S7  A combination of risk-taking behaviour towards colleagues and family members shows a comparable predictive performance as the best model. In detail, we define risk-taking behaviour with a threshold at the 70th percentile, calculate the PSIS-LOO score, which approximates the out-of-sample predictive performance, and rank the results from highest to lowest performing. We consider the score difference significant if it is larger than the 95% CI (approx. twice the standard error) and highlight rows with bold letters that show a non-significant performance difference to the best performing model. Here, the difference in LOO score is non-significant for all model.
Fig. S9  Negative cross correlation between pooled effect sizes highlights co-linearity of predictors. We compare risk-taking behaviour with a threshold at the 70th percentile towards different social groups: contacts to strangers, family members outside the household, friends, and colleagues. The diagonal shows raw posterior effect sizes. The upper non-diagonal fields give the Pearson’s correlation coefficient, whereas the lower non-diagonal fields present more details: a scatter plot of sampled effect sizes from two different predictors with contours of constant density and a linear regression line, which visualizes the correlation. The figure shows that pooled effect sizes for risk-taking behaviour towards strangers, friends, and colleagues are negatively correlated indicating co-linearity (see Fig. S8 for a visual comparison). Note that family and colleagues related effect sizes are positively correlated, thus indicating a combination of both time series. Indeed, we find that risk-taking behaviour towards colleagues and family members together have a similar predictive performance to the best model (see Fig. S7).
S8 Sensitivity analysis

Fig. S10 The LOO cross-validation results in Fig. 3 of the main text are not sensitive to minor variations in the observation window - Self reported survey is the best predictor for regional hospitalizations compared to the mobility data streams. Details: We compare the result from the main text (left panel) with a shifted observation window: The start and end date are shifted by +5 days and −5 days in the central and right panel, respectively.

Fig. S11 The LOO cross-validation results in Fig. 5 of the main text are not sensitive to minor variations in the observation window - Risk-taking behaviour towards friends demonstrates consistently the best predictive performance and risk-taking behaviour towards strangers performs only marginally worse. Details: We compare the result from the main text (left panel) with a shifted observation window: The start and end date are shifted by +5 days and −5 days in the central and right panel, respectively.
Fig. S12 The LOO cross-validation results in Fig. 3 of the main text are not sensitive to minor variations in the infection-to-hospitalization delay distribution - Self reported survey is the best predictor for regional hospitalizations compared to the mobility data streams, though Google performs only marginally worse in the middle panel. Details: We compare the result from the main text (left panel) with a modified infection-to-hospitalization delay distribution, where we shift the mean of the distribution (Weibull(shape=0.845, scale= 5.506); see Eq. 7) by +1 day (i.e., Weibull(shape=0.845, scale= 6.506)) and -1 day (i.e., Weibull(shape=0.845, scale= 4.506)) in the middle and right panel, respectively. Thereby we keep the shape parameter of the distribution constant.

Fig. S13 The LOO cross-validation results in Fig. 5 of the main text are not sensitive to minor variations in the infection-to-hospitalization delay distribution - Risk-taking behaviour towards friends demonstrates consistently the best predictive performance and risk-taking behaviour towards strangers performs only marginally worse. Details: We compare the result from the main text (left panel) with a modified infection-to-hospitalization delay distribution, where we shift the mean of the distribution (Weibull(shape=0.845, scale= 5.506); see Eq. 7) by +1 day (i.e., Weibull(shape=0.845, scale= 6.506)) and -1 day (i.e., Weibull(shape=0.845, scale= 4.506)) in the middle and right panel, respectively. Thereby we keep the shape parameter of the distribution constant.
**Fig. S14** The LOO cross-validation results in Fig. 3 of the main text are not sensitive to minor variations in the infection-to-hospitalization delay distribution - Self reported survey is the best predictor for regional hospitalizations compared to the mobility data streams. Details: We compare the result from the main text (left panel) with different choices for the threshold that defines risk-taking behaviour. We choose the 80th and 85th percentile in the middle and right panel, respectively. The thresholds correspond to at least 10, 15 and 19 reported contacts within the past 24h, respectively.

**Fig. S15** The LOO cross-validation results in Fig. 5 of the main text are not sensitive to minor variations in the infection-to-hospitalization delay distribution - Risk-taking behaviour towards friends and strangers demonstrate the best predictive performance. Details: We compare the result from the main text (left panel) with different choices for the threshold that defines risk-taking behaviour. We choose the 80th and 85th percentile in the middle and right panel, respectively. The thresholds correspond to the following number of contacts towards strangers, family members, friends and colleagues, respectively: 70th percentile: ≥ 1, ≥ 1, ≥ 1, ≥ 1. 80th percentile: ≥ 4, ≥ 2, ≥ 3, ≥ 3. 85th percentile: ≥ 5, ≥ 3, ≥ 4, ≥ 4