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Home alone? Effect of weather-induced behaviour on spread of SARS-CoV-2 in Germany

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In early 2020 the world was struck by the epidemic of novel SARS-CoV-2 virus. Like many others, German government has introduced severe contact restrictions to limit the spread of infection. This paper analyses effects of weather on the spread of the disease under the described circumstances. We demonstrate that regions reported lower growth rates of the number of the infection cases after days with higher temperatures, no rain and low humidity. We argue that this effect is channelled through human behaviour. The evidence suggests that “good” weather attracts individuals to outdoor (safer) environments, thus, deterring people from indoor (less safe) environments. Understanding this relationship is important for improving the measures aiming at combating the spread of the virus.

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1. Introduction

2020 is definitely a memorable year. One of the reasons to remember it is the worldwide outbreak of a novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The virus is believed to have zoonotic origins and is contagious in humans. It causes coronavirus disease 2019 (COVID-19), which is especially dangerous for some vulnerable population groups. This paper analyses how weather-induced human behaviour affected the spread of SARS-CoV-2 in Germany.

COVID-19 is not the first pandemic in history. However, its economic consequences can be really different from the past disease outbreaks. The Black Death killed between one-third and half of the European population in the 14th century, but is likely to have laid the foundations of today’s economic prosperity (Voigtlander and Voth, 2013). A sudden decrease in the labour force resulted into a rise in urbanisation and higher per capita incomes. The Spanish flu hit the world devastated by the First World War, so that a destructive effect of the virus on the economy was limited. Even the ongoing AIDS pandemic can have adverse economic effects. On the one hand, it is likely to reduce investment in physical capital (Lorentzen et al., 2008). On the other, the widespread infection can lower fertility and enhance per capita consumption (Young, 2005). In the 21st-century world, where human capital and international movement of people and goods play crucial roles, COVID-19 can cause devastating consequences for the world economy. Social distancing measures needed to reduce the death toll will inevitably decrease the output (Atkeson, 2020; Eichenbaum et al., 2020). However, a carefully designed policy can help to minimise both the economic burden and the number of deaths (Acemoglu et al., 2020). Our article shows that some behavioural aspects play an important role in the spread of SARS-CoV-2.

The literature linking human behaviour with epidemiology has not been established after the start of Covid-19 pandemic. A range of studies have demonstrated that behavioural choices are a key factor affecting the global epidemic of HIV/AIDS (e.g., Kremer, 1996; Lakdawalla et al., 2006; Dupas, 2011). Adda (2016) found that expansions of transportation networks and inter-regional trade increase the spread of viruses. Epstein et al. (2007) and Cauchemez et al. (2008) argue that international air travel restrictions and school closure, respectively, can slow down a pandemic of flu. At the moment economic literature devoted particularly to SARS-CoV-2 is growing rapidly. Fang et al. (2020), Krenz and Strulik (2021) and Maloney and Taskin (2020) argue that low human mobility during the pandemic could slow down the growth of the new number of infections. Kapoor et al. (2020) argue that early social distancing causes a large reduction in numbers of infections and deaths. This study goes a different way and focuses on the effect of rather “natural” variations in human behaviour due to weather conditions.
Germany was one of the first European countries hit by SARS-CoV-2. The first case of infection that occurred on its territory was registered already on 27th January (Der Spiegel, 2020). However, the epidemic started weeks later. The first public measure to restrict the spread of the virus – cancellation of all public events with more than 1000 participants – was out on 9th March. First bans on private gatherings were being introduced starting from 16th March depending on a Bundesländer.1 On 23rd March the country-wide ban on gatherings of more than two persons not living in a same household was declared (RKI, 2020b). This restriction was still in act by the end of April 2020, when the study period of our article finished. A range of studies evaluates efficiency of policies introduced by the German government. For example, Dehning et al. (2020) and Donsimoni et al. (2020) used theoretical models to show that social distancing measures were generally efficient to reduce the number of new cases. Mitze et al. (2020) argue that face masks reduced the daily growth rate of new infections by around 47 percent. In our study we argue that variations in human behaviour still affect the spread of SARS-CoV-2 even if we control for all potential interventions from the government.

The relationship between weather and human behaviour has been documented long before the pandemic: people prefer to go out on days with high temperatures and no rain, and stay home otherwise (Graft Zivin and Neidell, 2014; Graham and McCurdy, 2004; McCurdy and Graham, 2003).2 Furthermore, people have longer contacts, if the temperature is low (Willem et al., 2012). Smieszek (2009) develops a theoretical model explaining why longer contacts are potentially more contagious. In 2020 the link between weather and human behaviour has become extremely important, as modality of human interactions affected the spread of SARS-CoV-2. Nishiura et al. (2020) argue that COVID-19 had 18.7 times higher odds of transmission in a closed environment compared to outdoors.3 Willem et al. (2012) provide evidence that many infections spread faster if people congregate indoors when the weather is bad. Liao et al. (2005) show that influenza and SARS – diseases with transmission mechanisms similar to COVID-19 – are significantly more contagious indoors. All this evidence allows us to expect that individuals were more likely to choose outdoor (safer) activities on days with “good” weather and outdoor (more contagious) ones on days with “bad” weather.

We are aware that many viruses can be affected by weather conditions directly. This paper does not try to oppose this fact. Instead, we argue that, additional to biological mechanisms, weather could mediate human behaviour in a way that had a significant effect on the spread of SARS-CoV-2. We have several reasons to consider this relationship. First of all, the evidence suggests that SARS-CoV-2 can be different to other seasonal coronaviruses in terms of transmission (Fernández-Raga et al., 2021). Cai et al. (2020) argue that indirect transmission via fomites (e.g., doorhandles, coins or restroom taps) is possible. This implies that the importance of weather can be relatively lower compared to viruses that are transmitted solely through droplets. Riddell et al. (2020) conducted a laboratory experiment that showed that at 30 °C an infectious virus was recoverable for up to 7 days from stainless steel or 21 days from paper notes. For example, the maximum temperature observed in our sample was 22 °C. Secondly, we provide evidence that people spend more time indoors, when the weather is bad. The temperatures in indoor environments are subject to much lower variation due to insulation and heating technologies. Thirdly, we can consider dynamics observed in other countries. For example, in Brazil the daily incidence was gradually rising from November 2020 till the middle of January 2021, even though this is a period when temperatures are rising in the Southern hemisphere. In India daily incidence was increasing during both summer and monsoon season, reaching the peak in mid-September, when daily temperatures throughout the largest part of the country were higher than those observed in our sample. Finally, we utilise temporal and spatial variations in imposed contact restrictions to argue in favour of the behavioural link. Particularly, we consider a full contact ban as an intervention that was designed to regulate human behaviour and, unlike temperature, had no direct effect on the virus. We provide evidence that “bad” weather and the full contact ban affect personal mobility in similar ways: they increase the number of visits to places of residence at the expense of less visits to parks. This explains why we also observe similar effects on the spread of SARS-CoV-2: the full contact ban and lower temperatures are associated with a faster growth of new infections.

The severity of every epidemic depends on a number of aspects. As economists we are primarily interested in those factors that humans can control. The main goal of the government during the outbreak of an infectious disease is regulating human behaviour in a way that would reduce the number of potentially contagious social contacts. However, before introducing these measures, it is important to understand what aspects of our behaviour promote or halt the spread of the virus in general. In other words, even absent any regulation from the state people have habits that can affect the growth rate of the number of disease cases. Understanding these patterns is important for an efficient policy that allows to tackle the epidemic at lower economic, social and emotional costs. This paper can also help to understand potential weaknesses of contact restrictions imposed by the German government. Although social contacts during the epidemic were severely restricted, it is impossible to ban them completely. Blom et al. (2020) suggest that almost half of the German population was having some social contacts during the study period. We demonstrate that weather could be one of the factors that affected the modality of these interactions. Thus, a policy encouraging more outdoor contacts at the price of indoor ones appears to be logical to slow down the spread of SARS-CoV-2. Moreover, these findings provide a simple, yet practical explanation for the second wave of the epidemic that Germany and other European countries have faced in autumn 2020–winter 2021, when human activities naturally moved indoors.

Overall, we demonstrate that (a) weather had a significant effect on the spread of SARS-CoV-2; (b) this effect is robust to a use of other weather characteristics; (c) the effect varied significantly with a time of a weather record; (d) weather significantly affected human mobility patterns in way that is expected to affect the progress of SARS-CoV-2; (e) the effect of the weather on the spread of the virus was significantly different during and absent contact restrictions. We consider that these findings jointly support the hypothesis that besides the direct effects on a virus, weather also affected human behaviour in a way that had could influence the spread of SARS-CoV-2.

This paper is organised as follows. First, we explain our way to measure the spread of SARS-CoV-2 and develop a simple theoretical application. Then, we adjust it for the empirical testing and describe the methodology and data used. Section 4 presents the results of regressions aiming to explain the spread of the disease with weather fluctuations. Section 5 empirically analyses personal mobility during epidemic. Section 6 is devoted to the empirical analysis of the effect of weather on the spread of

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1 Bundesland (plural Bundesländer) is a federated state of the Federal Republic of Germany. It corresponds to NUTS 1 level of administrative units in Europe. There are 16 Bundesländer in Germany.
2 Graft Zivin and Neidell, 2014 find a non-linear relationship between time spent outdoors and air temperature, but the significant negative effect is observed for values above 30 °C. All observations in our sample are below this threshold.
3 This article was not peer-reviewed by the time our paper was finished.
SARS-CoV-2 particularly under contact restrictions. Finally, a brief conclusion completes the paper.

2. The model

The SEIR model is available to analyse various infection outbreaks, like HIV, Ebola or COVID-19. This model (or more accurate, class of models) allows to estimate several important parameters that are required for understanding a disease. For the purposes of our research we employ one of the equations of the model to estimate the growth rate of the number of infections. The evolution of the number of cases diagnosed with the disease can be described with a simple differential equation:

\[
  \alpha l = (1 - \alpha)\gamma r + \alpha\gamma_l - (1 - \alpha)\frac{1}{\gamma} - \alpha\frac{1}{\gamma}. \tag{1}
\]

\( l \) is the total size of the currently infected population and \( \alpha \) is the share of infected with revealed symptoms. Ing et al. (2020) argue that the share of infected individuals without any symptoms can be large, so there is a high chance that many of those who had been infected never realised this fact. As a result, we assume that only symptomatic cases (\( \alpha l \)) were registered. Nevertheless, asymptomatic cases (\((1 - \alpha)l\)) can be contagious and an infected individual generates \( r \) new cases. Each infected individual is assumed to be contagious only for a certain period of time: \( \gamma \) is the mean communicability period for asymptomatic cases* and \( \gamma_h \) is the mean time from infection to isolation of individuals with symptoms (e.g., in hospital). The last two characters in Eq. (1) stand for recovery of asymptomatic and symptomatic individuals, respectively. The classical SEIR model also assumes that not all individuals can be infected with a disease. For example, those who were infected in the past and have already recovered are likely to develop immunity, at least, for a while. Thus, not all social contacts have a potential to initiate a new infection case, but only a share of those, who are generally susceptible. This article considers the sample period that ended on 30th April 2020. By this time 163 thousand cases of COVID-19 were registered in Germany, what is roughly equal to 0.2 percent of the total population (RKI, 2020a). Even though it is not yet exactly known what share of infected does not reveal symptoms, we have reasons to believe that the real number of infected individuals has not substantially exceeded 1 percent of the total population (Mizumoto et al., 2020). Hence, we approximate the share of susceptible contacts to one. Nevertheless, Eq. (1) accounts for the fact that not all infected with SARS-CoV-2 develop symptoms, despite being contagious.

We can rearrange Eq. (1) as:

\[
  \alpha l = l\lambda, \text{ where } \lambda = \frac{r((1 - \alpha)\gamma + \alpha\gamma_l)}{\gamma} - (1 - \alpha)\gamma_h - \alpha\gamma, \tag{2}
\]

Assuming the share of cases that reveal symptoms to be constant, the solution to Eq. (1) is:

\[
  \alpha l(t) = \alpha l(0)e^\lambda t, \text{ where } y(t) = \int \lambda(t)dt. \tag{3}
\]

and \( l(0) \) is the initial number of infected. Given that SARS-CoV-2 has emerged outside Germany, \( l(0) \) can also be treated as a number of cases imported to a region. It has to be noted that Eq. (1) ignores further interregional contacts and models transmissions only within a region. This is a strong assumption, if we focus only on the initial stages of the spread of the disease. However, the majority of cases was registered (and most likely infected) already after the contact restrictions were introduced (RKI, 2020b). Thus, we assume that the largest share of transmissions occurred within regions. In the empirical section we demonstrate that our results are robust to spatial autocorrelation.

Eq. (3) describes the number of cases, that had symptoms and were registered. We could rearrange it to obtain the “true” number of infections, but this gives no benefit for the purpose of this research, as the data endows us exactly with the number of recorded cases.

3. Empirical estimation

Eq. (3), as it is formulated now, allows us to use the existing data to estimate the exponential growth rate of the number of recorded cases from the first known occurrence of the disease until date \( t \) (\( y(t) \)). However, this might be not practical, if we want to analyse the evolution of this variable. Later estimates of \( y(t) \) would also account for all of its previous evaluations. However, existing studies of SARS-CoV-2 suggest that the incubation period of the infection does not exceed 14 days (Backer et al., 2020). Relying on this information we can be certain that individuals diagnosed with COVID-19 today were not infected 15 days ago or earlier. In other words, the initial cases have no direct effect on infections that were registered 15 days after them and must be intermediate cases in between. Thus, we can treat \( l(0) \) as a dynamic variable. For each day \( t \) we have a particular \( l_0(t) \) that marks the number of cases that infected (in a timespan between 1 and 14 days ago) individuals diagnosed with COVID-19 on this day. Existing studies suggest that the incubation period of SARS-CoV-2 varies among individuals. This implies that all people were infected on different days. Backer et al. (2020) provide the distribution function of incubation periods. We weight past registered cases according to the probability that they transmitted the infection to the cases registered on day \( t \). As a result, we obtain \( \hat{l}_0(t) \) – the expected number of cases that infected \( l(t) \) cases.

Once we calculate \( \hat{l}_0 \), we can use it to estimate \( y(t) \), that will tell us how fast new cases were emerging from one case in the course of 14 days. We obtain it by transforming Eq. (3):

\[
  \log(\alpha l(t)) - \log(\alpha \hat{l}_0(t)) = y(t). \tag{4}
\]

This time span is already shorter and allows us to see the effect of particular events that affected the spread of the disease much clearer. However, when we analyse the effect of past weather variations, we also have to account for the fact that contagion could take place up to 14 days ago. For this reason, we apply the same approach as described above: we calculate a moving average of weather observations in the previous 14 days, weighted according to the probability that cases of today were infected on that day. By doing so we give higher significance to days, when infections were more likely to happen.

We have to address the distribution of estimated \( y(t) \) and temperature across time and space. The structure of our dataset allows to explore variation both between and within German regions. However, to be able to control for all unobserved heterogeneity between localities, we employ a fixed effects estimator. This allows us to analyse evolution of infection cases as a function of an exogenous factor – weather. We do not explicitly address such characteristics of regions, as demography, social cohesion or access to mobility infrastructure, but take it into account with regional fixed effects. As will be demonstrated later a larger part of variation in our dataset appears within regions across time, so we partial out only a smaller part of total variation.
Another important concern is evolution of $y(t)$ over time. Fig. 1 demonstrates that the growth of number of new cases was slowing down throughout our sample period, but this process was going rather smoothly. For example, we see no sudden changes after 23rd March, when country-wide contact restrictions were installed. Nevertheless, the presence of a clear trend in our variable of interest can lead to a potential simultaneity bias. However, we see no clear linear trend for an average weather observed in the country. Finally, we remove the trend by adding respective time-fixed effects. We also allow for separate intercepts for each Bundesland-date level.

3.1. Methodology and data

Once we have developed the methodology for calculation of our variables of interest we employ several sources to obtain the dataset. Data on the number of infections are provided by Robert Koch Institute (RKI). This is a German federal government agency and research institute responsible for disease control and prevention. Number of new COVID-19 cases is recorded every day by a health department of each of 401 Landkreise. \(^1\) Local health authorities receive information from hospitals and doctor's practices about each COVID-19 case diagnosed. Later this information is transferred to a health authority of a respective Bundesland and finally goes to RKI. As a result, information about each infection case arrives to RKI with some delay (typically, a few days). Then, RKI reports all cases on the day they arrive, regardless of the actual start of the disease. Nevertheless, the RKI dataset includes the date when each disease case started. These particular dates are referred to as a time dimension for this paper. That is why the dataset used might have slight differences to official daily reports published by RKI. Fig. 2 presents spatial distribution of COVID-19 cases registered in Germany.

The weather data are provided by the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR). This is a geo-coded dataset with a resolution of 1km that provides values of a wide set of parameters four times per day: at 0:00, 6:00, 12:00 and 18:00. For all weather characteristics we have first calculated simple spatial averages of each variable at the level of Landkreis. Given a fairly small size of German regions (an average Landkreis has a land surface of less than 900 km\(^2\)), simultaneous weather observations within each Landkreis are highly correlated (if not exactly similar). For our main variable of interest – temperature – we select the maximum value out of the four observations taken on a particular day, but results are robust to alternative proxies (e.g., mean). Summary statistics of all used variables are presented in Table A1. Fig. 3 demonstrates how temperatures varied across regions in Germany.

Table 1 compares the variance of our main variables of interest: growth rate of new cases and temperature. Both variables have mostly varied within Landkreis. In case of $y(t)$ this pattern is explained by the fact that all regions have experienced a rather similar evolution of the number of infection cases: starting from no infections, then rapid growth in the number of infected and a subsequent slowdown. Local characteristics like population density, demography or testing capacities affected the absolute values, but within each Landkreis the time changes were more pronounced. Temperatures also mostly vary within regions, as all of them experienced gradual transition into the summer. This distribution of variation serves as another justification for the choice of a FE estimator.

Overall, our sample covers the data from 1st March till 30th April 2020, when the most acute phase of the “first wave” of the epidemic was observed in Germany. Focusing on this time period has a number of reasons. First of all, we use the theoretical application of the paper assumes that the whole population is susceptible. This is a plausible assumption for the first days of the epidemic. However, as the virus was progressing, more and more people were getting over COVID-19 and developed immunity. By 30th April 2020 Germany had registered around 160,000 infection cases. Even under the boldest assumptions about the share of asymptomatic cases, the total number of infections should remain below one percent of the total population. At later stages we would need to factor in a share of population that has become immune (and then possibly lost the immunity at some point). This is not an easy task, given a very mixed evidence on the possibility of reinfecction (Tillett et al., 2021). Moreover, we do not address the issue of various mutations of SARS-CoV-2 that are more likely to happen as the pandemic progresses. The first variant of SARS-CoV-2 that was considered a serious threat was found in August 2020 and was linked farmed minks in Denmark (WHO, 2020). We focus on the period when SARS-CoV-2 was considered a relatively homogeneous virus.

It is natural to expect that heterogeneity (e.g., age composition of the population) between regions can bias our empirical results. For this reason we include Landkreis-level fixed effects. To demonstrate that the effect of weather on the spread of SARS-CoV-2 is causal, we have to rule out the possibility that both weather and $y(t)$ are driven by a common (omitted) factor. As was demonstrated previously, the longer we are aware of the virus, the slower it progresses: e.g., individuals master their ways to avoid infection. However, the closer it gets to the summer, the warmer it
Fig. 2. Regional distribution of COVID–19 infections in Germany. COVID–19 infections by 30th April 2020 (per 100,000 people).
As a result, time simultaneously affects both spread of the virus and weather. Besides that, we have to account for differences in official measures to prevent the spread of the disease, such as contact restrictions. In Germany the decisions on particular rules were mostly taken by governments of each of 16 Bundesländer independently. Even though the list of measures was quite similar, the timing of their onset was different. For example, the state of Bavaria introduced a curfew starting from 17th March, while not all regions used this measure. Instead, a country-wide ban on gatherings of more than two people was introduced on 22nd March. That is why we control for heterogeneous time trends for each Bundesland by adding date \times Bundesland fixed effects. The latter combination of fixed effects slightly reduces our sample, as two Bundesländer in Germany consist of only one Landkreis (Berlin and Hamburg). However, as will be demonstrated later, the results are not driven by sample differences. When it is necessary to study differences between particular measures aiming to

Table 1

| Variable          | Mean | Standard deviation |
|-------------------|------|--------------------|
| \( y(t) \)       | 0.392| 0.431              |
| Temperature       | 13.448| 4.187             |

gets. As a result, time simultaneously affects both spread of the virus and weather. Besides that, we have to account for differences in official measures to prevent the spread of the disease, such as contact restrictions. In Germany the decisions on particular rules were mostly taken by governments of each of 16 Bundesländer independently. Even though the list of measures was quite similar, the timing of their onset was different. For example, the state of Bavaria introduced a curfew starting from 17th March, while not all regions used this measure. Instead, a country-wide ban on gatherings of more than two people was introduced on 22nd March. That is why we control for heterogeneous time trends for each Bundesland by adding date \times Bundesland fixed effects. The latter combination of fixed effects slightly reduces our sample, as two Bundesländer in Germany consist of only one Landkreis (Berlin and Hamburg). However, as will be demonstrated later, the results are not driven by sample differences. When it is necessary to study differences between particular measures aiming to

Table 2

| Dependent variable | \( y(t) \) |
|--------------------|-----------|
|                   | (1)       |
| Past max daily temp. | -0.059***|
|                    | (0.001)   |
| Past infections    | -0.067***|
|                    | (0.001)   |
| Within R-squared   | 0.333     |
| \( N \) of Landkreise | 401     |
| \( N \) of obs.    | 18,847    |
| Landkreis FE       | No        |
| Date FE            | No        |
| Date \times Bundesland FE | No |

OLS regressions. Temperature measure employed is a past weighted daily maximum. All regressions include a constant term. Data are from RKI and CFSR. Standard errors clustered at the Landkreis level in parentheses.

* \( p < 0.10 \)
** \( p < 0.05 \)
*** \( p < 0.01 \)

Fig. 3. Regional distribution of average daily maximum in Germany.
increase social distancing we use the data by Steinmetz et al. (2020).

Germany is a country with a relatively high population density and developed infrastructure. This allows many people to travel between Landkreise on a regular basis. Thus, we cannot ignore spatial autocorrelation of the infection rates between the regions: high number of new cases in one area is likely to affect the epidemiological situation in neighbouring areas. We assume two possible relationships between our explanatory variables (e.g., air temperature) and the spread of the disease, described by the autoregressive spatial (SAR) and the Durbin spatial (SDM) models (Lesage and Pace, 2009). Generally, both models can be presented by Eq. (5):

$$y_t = \rho W y_{t-1} + \beta x_t + \chi_{\theta} + \epsilon_t,$$

where $\rho$ is the spatial autoregressive parameter, $W$ is the spatial matrix (we use two different matrices: contiguity and inverse distance), $\beta$ is the parameter for exogenous explanatory variables, $\chi_{\theta}$ captures the effect of spatially lagged explanatory variables and $\epsilon$ is an error term. SAR model assumes no exogenous effect of spatially lagged explanatory variables on the dependent variable (i.e., $\theta = 0$). This specification relies on the assumption that weather in neighbouring Landkreise affects the spread of the disease only through the number of new infections in respective regions and not through other channels. If we allow for the direct effect of weather in surrounding regions on the number of new cases in a Landkreis, we use SDM (i.e., $\theta \neq 0$). However, later we demonstrate that the difference between the two models is not dramatic, as German Landkreise are not large enough to provide substantial variations in weather conditions between neighbouring regions.

4. Effects of weather on spread of SARS-CoV-2

4.1. Temperature and spread of disease

To start with, Table 2 demonstrates that temperature has a significant effect on the exponential growth rate of disease cases. The effect is robust to inclusion of different sets of fixed effects. The results suggest that we observe slower spread of COVID-19 in a region, if the temperature was higher at the time, when infections were most likely to happen. Moreover, this effect is non-negligible: on average a 2°C increase in maximum daily temperature would translate into an 11 percentage points lower exponential growth rate. This finding goes in line with the epidemiological literature cited above and suggesting that diseases spread faster, when weather conditions prevent individuals from going outside. The residual scattergram presented in Fig. A1 shows that after we partial out the effects of common time trend and unobserved heterogeneity between Landkreise, our variables of interest are rather normally distributed and the significant relationship between them is not determined by a single Landkreis or Bundesland.

Our dependent variable is a growth rate that ignores a current level of infections. For example, a change from 2 to 4 cases would imply the same growth rate as 100 to 200. To control for potential convergence or divergence of growth rates, we also include the past number of infections ($I_0$) as a control variable. Results of this set of regressions presented in column (5) demonstrate very little changes compared to other results in Table 2. Finally, we have to address changes in a within-R-squared. As was expected, evolution of $y(t)$ is subject to a time trend, so when we control for it, predictive power of our model significantly reduces. Nevertheless, even after controlling for simultaneity of temperature and the dependent variable we still observe significant relationship.

4.2. Controlling for spatial autocorrelation

As was mentioned above, we cannot ignore spatial autocorrelation between the number of new disease cases. Results obtained using spatial econometric models are presented in Table 3. Estimated coefficient $\rho$ supports the hypothesis that numbers of new infection cases are significantly positively correlated between Landkreise. This relationship holds for all models and weighting schemes. Besides that, both SAR and SDM allow to distinguish between total and direct effects of weather. In our setting the direct effect captures the weather observed in a particular Landkreis, while the total effect also accounts for weather observed in neighbouring Landkreise (when contiguity spatial matrix is used) or the whole country (inverse distance matrix). Given that weather observations are spatially correlated, both effects support our initial hypothesis: past temperature (both in a Landkreis and around it) significantly negatively affects the spread of SARS-CoV-2.

Table 3

| Dep. variable: y(t) | SAR | SDM |
|---------------------|-----|-----|
| Estimator:          |     |     |
| Spatial weighting:  |     |     |
| Contiguity          |     |     |
| Inverse distance    |     |     |
| Direct temp.        |     |     |
| Contiguity          |     |     |
| Inverse distance    |     |     |
| Total temp.         |     |     |
| Contiguity          |     |     |
| Inverse distance    |     |     |
| $\rho$              |     |     |
| E-squared            |     |     |
| N obs.               |     |     |
| Landkreis FE        |     |     |
| Date FE             |     |     |

| Variable            | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| $\rho$              | -0.01261*** | -0.1129*** | -0.00245*** | -0.01135*** | -0.00138 | -0.00661 | -0.01432*** | -0.01676*** |
| (0.00105)            | (0.00179) | (0.00044) | (0.00187) | (0.00628) | (0.00503) | (0.00210) | (0.00330) |
| Total temp.         | -0.06567*** | -0.05144*** | -0.08211*** | -0.07189*** | -0.06648*** | -0.01615*** | -0.07638*** | -0.02812 |
| (0.004578)          | (0.00232) | (0.01999) | (0.01411) | (0.00431) | (0.00270) | (0.02023) | (0.07352) |
| $\rho$              | 0.85433*** | 0.26651*** | 0.97223*** | 0.84339*** | 0.85401*** | 0.26651*** | 0.97497*** | 0.84527*** |
| (0.00633)           | (0.02006) | (0.00459) | (0.01852) | (0.00632) | (0.02006) | (0.00421) | (0.01805) |
| E-squared            | 0.355 | 0.395 | 0.407 | 0.408 | 0.398 | 0.396 | 0.407 | 0.401 |
| N obs.               | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 |
| Landkreis FE        | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Date FE             | No | Yes | No | Yes | No | Yes | No | Yes |

Temperature measure employed is a past weighted daily maximum. All regressions include a constant term. Data are from RKI and CFSR. Standard errors clustered at the Landkreis level in parentheses.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$. 

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4.3. Other weather characteristics and spread of disease

Nevertheless, we need to support our claim that the effect of “good” weather on the spread of SARS-CoV-2 is driven by human behaviour and not natural factors. For example, we cannot rule out the possibility that the virus might stay viable longer in cold conditions. First, we argue that similar effects are observed for other weather characteristics that can potentially affect the decision to go out or stay indoors. CFSR provide a set of characteristics that can be suitable for this purposes. We employ rain, humidity and sensible heat flux at the surface. Rain is a categorical variable, taking value of 1 if it was raining in the area at the moment of recording the weather. The average of these values across a Landkreis territory can be interpreted as a share of the total area on which it was raining. For the regression analysis we calculate a simple average of these shares across the four time periods of data recording. Humidity and heat flux are both continuous variables, however we aggregate them differently. Humidity is first calculated as an average across a Landkreis, then as an average across four recording times. Sensible heat flux is first averaged at the Landkreis level and then we take a maximum value of the four time periods. The results of estimations with alternative weather measures presented in Table 4 support the main hypothesis of the paper: “better” weather is associated with slower spread of the disease.

4.4. Differential effects of temperature on spread of disease

Estimates presented so far support the statement that “better” weather is associated with slower spread of SARS-CoV-2. However, all weather characteristics used above can still be correlated with temperature and have a direct effect on the virus. As an alternative way to argue that the effect comes through human behaviour, we utilise the intra-day temperature variations. Even though the temperature measures at different times correlate, this is not a mechanical relationship (see Table A2). It is logical that weather at different times of a day affects social contacts differently. That is why we compare the effects of temperature recorded at different times. Results presented in Table 5 suggest that temperature affects the growth rate of number of infections only at a particular time of a day. Interestingly, while temperature at 12:00 indicates a negative effect on \( y(t) \), observations made at other times demonstrate no significant relationship. One potential explanation to this pattern is that people could evaluate the weather of a particular day at around noon and make according plans during this time. At night and early morning people generally sleep or occupied with their daily routine and weather has no effect on their socialisation, as suggested by the insignificant coefficients of the temperature measured before 12:00. Then, during the day and early evening people are typically more active socially and the weather mediates where they socialise: higher temperatures make meetings outdoors more attractive, thus, decrease the infection potential of social contacts. This line of arguments implies that weather can determine where people interact. If the weather effect had an exclusively biological nature, we would expect significant coefficients throughout the whole day.

5. Personal mobility during epidemic

So far we have argued that weather affects, where people have social interactions. To support this claim we use Community Mobility Report by Google LLC (2020), Google tracks location history of all Android devices that have enabled the respective function. The company does not provide information about the exact number of devices that share their data, but we expect it to be large enough. Ruktanonchai et al. (2018) conducted international nationally population-representative surveys that indicated the share of users having deliberately enabled the location tracking between 43 percent in Japan to 72 percent in Mexico. Moreover, the share of those who had disabled this function did not exceed 18 percent, and a substantial share did not know whether they have enabled it. Unfortunately, Germany was not part of the survey, but we have evidence that the share of Android users is large in the country. According to Kantar (2021) in May 2020 more than three quarters of mobile phones sold in Germany were Android devices. Overall, close to 60 million adults in

| Table 4 | Past weather and spread of disease. |
|---|---|
| **Dependent variable:** y(t) | **Weather characteristic:** | **Humidity** | **Heat flux** |
| | Rain | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Past weather** | | | | | | |
| 0.627*** | 0.136*** | 0.045*** | 0.011*** | –0.016*** | –0.001 |
| (0.011) | (0.067) | (0.001) | (0.005) | | |
| **Within R-squared** | | | | | | |
| 0.130 | 0.001 | 0.748 | 0.004 | 0.633 | 0.000 |
| **N of Landkreise** | 400 | 398 | 401 | 399 | 401 | 399 |
| **N of obs.** | 17,200 | 17,114 | 17,243 | 17,157 | 17,243 | 17,157 |
| **Landkreis** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Date > Bundesland FE** | No | Yes | No | Yes | No | Yes |

OLS regressions. All regressions include a constant term. Data are from RKI and CFSR. Standard errors clustered at the Landkreis level in parentheses.

* \( p < 0.10 \)
** \( p < 0.05 \)
*** \( p < 0.01 \)

| Table 5 | Differential effects of past temperature and spread of disease. |
|---|---|
| **Dependent variable:** y(t) | **Record time:** |
| | 00:00 | 06:00 | 12:00 | 18:00 |
| | (1) | (2) | (3) | (4) |
| **Past temperature** | 0.009 | 0.003 | –0.023*** | –0.009 |
| | (0.007) | (0.009) | (0.006) | |
| **Within R-squared** | 0.001 | 0.000 | 0.007 | 0.001 |
| **N of Landkreise** | 399 | 399 | 399 | 399 |
| **N of obs.** | 18,753 | 17,157 | 17,955 | 18,753 |
| **Landkreis FE** | Yes | Yes | Yes | Yes |
| **Date > Bundesland FE** | Yes | Yes | Yes | Yes |

OLS regressions. All regressions include a constant term. Temperature measure employed is a past weighted average recorded at the respective time. Data are from RKI and CFSR. Standard errors clustered at the Landkreis level in parentheses.

* \( p < 0.10 \)
** \( p < 0.05 \)
*** \( p < 0.01 \)
Germany are smartphone users (Statista, 2020). Even if some selection into Android users in terms of income and age took place, the sheer number of devices is large enough to make claims about a substantial share of the German population.

Google Community Reports provide data on the percentage changes in a number of visits to places in a given geographic area. As the baseline it uses “the median value for the corresponding day of the week, during the five-week period 3rd January–6th February 2020” of a respective region. Thus, we can expect some natural mobility trends in the dataset: e.g., people always go to parks more in spring and summer than in winter. We control for this including date fixed effects. The Community Mobility Reports data are aggregated at the Bundesland level, higher than the one of infections data. To adjust weather observations we calculate population-weighted spatial averages, so Landkreise with more residents have a higher weight in our calculation. To account for time-invariant heterogeneity between Bundeslaender (e.g., demography or infrastructure) we include Bundesland-level fixed effects. Community Mobility Reports split places of visit into six following categories: supermarkets and pharmacies, parks, public transport hubs, retail and recreation, residential and workplaces. For this study we are primarily interested in parks and places of residence. Normally, we expect more visits to parks and less to residential areas on days when the weather is “good” and vice versa. However, we have to account for the fact that individual mobility was restricted by the state during the epidemic. For example, some Bundeslaender (e.g., Bavaria) prohibited to stay in public space in the company of people who do not belong to the same household (full contact ban), while others never introduced this measure (e.g., Lower Saxony). Overall, 27 percent of Landkreise in Germany have experienced a contact ban. Fig. 4 demonstrates spatial allocation of the full contact ban across the country. To analyse the effect of this restrictions we employ a dataset by Steinmetz et al. (2020) that provides information on all measures installed to ensure social distancing. In Germany particular restrictions were introduced by the government of each Bundesland separately allowing us to analyse two levels of variation: time and regional. Results of this set of regressions are presented in Table 6.

Results presented in Table 6 provide evidence that both weather and contact ban significantly affect, where people interact. Even after we control for a time trend, high temperature still attracts more people to parks. In other words, warmer days experienced larger relative change to the winter reference period than colder ones. At the same time, contact ban reduces the relative number of visits. Furthermore, temperature attracts people to parks at all times, but this effect is significantly smaller during the contact ban. Places of residence demonstrate the reversed relationship: cold

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6 As “parks” Google defines places such as local parks, national parks, public beaches, marinas, dog parks, plazas and public gardens.

7 Later in this paper by “contact ban” we mean prohibition of all contacts between non-household members.
Table 6
Weather and changes in personal mobility.

| Dependent variable: | \( \Delta \text{parks} \) | \( \Delta \text{places of residence} \) |
|---------------------|-----------------|-----------------|
|                     | (1)             | (2)             | (3)             | (4)             | (5)             |
| Temperature         | 3.996***        | 4.221***        | -0.085***       | -0.093***       | -0.028          |
|                     | (0.362)         | (0.363)         | (0.022)         | (0.022)         | (0.023)         |
| Contact ban         | -15.862***      | 3.569           | 1.792***        | 1.141***        | 1.195***        |
|                     | (2.925)         | (5.252)         | (0.225)         | (0.342)         | (0.299)         |
| Temperature \times contact ban | -1.528*** | (0.346)         | 0.051***        | 0.028           | 0.019           |
| \( \Delta \text{parks} \) |                   |                 |                 |                 | -0.015***       |
|                     |                 |                 |                 |                 | (0.003)         |

FE regressions. Temperature measure employed is an average daily maximum. All regressions include a constant term, Bundesland and date fixed effects. Data are from Google and CFSR. Robust standard errors in parentheses.

* \( p < 0.10 \).

** \( p < 0.05 \).

*** \( p < 0.01 \).

Table 7
Social distancing measures and individual mobility.

| Dependent variable: | Change in visits to places of residence |
|---------------------|----------------------------------------|
|                     | (1)         | (2)         | (3)         | (4)         | (5)         | (6)         | (7)         |
| Contact ban         | 1.728***    |             |             |             |             |             | 1.586***    |
|                     | (0.445)     |             |             |             |             |             | (0.234)     |
| Contact restrictions|             | 0.564*      |             |             |             |             | 0.402       |
|                     |             | (0.313)     |             |             |             |             | (0.277)     |
| 1.5 m distance      |             |             | 0.516       |             |             |             | 0.327       |
|                     |             |             | (0.305)     |             |             |             | (0.202)     |
| Prohibition to leave home |             |             |             | 0.474       |             |             | 0.192       |
|                     |             |             |             | (0.679)     |             |             | (0.167)     |
| Daycare facilities closed |             |             |             |             | 0.566       |             | -0.082      |
|                     |             |             |             |             | (0.385)     |             | (0.376)     |
| Schools closed      |             |             |             |             |             | 1.111***    | 1.035***    |
|                     |             |             |             |             |             | (0.467)     | (0.514)     |
| Adj. R-squared      | 0.054       | 0.004       | 0.007       | 0.012       | 0.003       | 0.005       | 0.065       |
|                     | (0.467)     | (0.202)     | (0.299)     | (0.023)     | (0.023)     | (0.023)     | (0.023)     |
| N of Bundeslaender  | 16          | 16          | 16          | 16          | 16          | 16          | 16          |
| N of obs.           | 976         | 976         | 976         | 976         | 976         | 976         | 976         |

FE regressions include a constant term, Bundesland and date fixed effects. Data are from Google and Steinmetz et al. (2020). Robust standard errors in parentheses.

* \( p < 0.10 \).

** \( p < 0.05 \).

*** \( p < 0.01 \).

Weather and contact ban drive more people to indoor environments. However, as column (5) demonstrates, the effect of weather on visits to residential areas most likely comes through its effect on parks.\(^8\) One possible explanation to this pattern is that if people find it not comfortable to meet outdoors, they are more likely to socialise at home. Another important result presented in Table 6 is the overall effect of contact ban on individual mobility: even if it can reduce the number of contacts, it is likely to drive them indoors, thus, making them more dangerous. We explain this with the fact that people cannot fully neglect social interactions in person and in 2018 there more than 17 mil. single-person households in Germany (Statistisches Bundesamt, 2019). As a result, when social contacts were prohibited in public, homes remained the only place where people could meet. Moreover, to argue that this was a response particularly to the contact ban we analyse how other measures affected visits to residential areas.

Table 7 presents the effects of selected social-distancing measures on the change in a number of visits to places of residence. Besides a ban on contacts of different households, many Bundeslaender have introduced restrictions on a number of people who meet simultaneously (e.g., only two households, not more than ten people). This measure has no effect on visits to places of residence, when we control for the general contact ban. As expected, introduction of 1.5 m distance in public spaces or prohibition to leave home without sound reason did not significantly affect visits to places of residence. If we focus on social interactions of children, we see that daycare facilities closure had no effect on visits to residential areas, as little children cannot leave home without parents, who are likely to be busy working. However, closing schools increased the number of visits to residential areas, as school-age children could compensate lack of social interactions in a classroom by paying visits to friends.

It has to be noted that indoor environments per se are not contagious, but social contacts indoors are. For this reason we need to argue that visits to residential areas are associated with social interactions. First of all, our mobility measure shows a relative change in a number of visits, so a daily routine, such as coming back from work, should not be affected by it. At the same time, meeting a friend or a relative at her or his apartment will increase this value, if previously you used to meet in public, e.g., in cafes or parks. Overall, we see evidence that “good” weather attracted more

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\(^8\) Alternative weather characteristics have demonstrated similar effects on mobility. Results of these regressions are presented in Table A3.
people to safer outdoor environments, while “bad” weather drove them indoors. It is important to note that the contact ban reduced the effect of weather on visits to parks and increased the number of visits to residential areas. It is possible that the overall number of social contacts has decreased, but their nature has become more epidemiologically unsafe. That is why in the next section we evaluate the effect of contact ban on the spread of SARS-CoV-2.

6. Weather and spread of disease under contact restrictions

Results presented so far suggest that “good” weather slows down the spread of SARS-CoV-2. We provide evidence that this effect, at least partially, can come through the human behaviour. “Good” weather attracts people to outdoor environments that have lower infection potential, thus, deters visits to residential areas, where people are likely to meet, when social contacts in public are prohibited. If this is the case, we should observe differential effects of weather on the growth rate of new cases under and absent the full contact ban. We expect that a ban on social contacts in public could have an adverse effect on the spread of SARS-CoV-2: if it provoked new visits to residential areas, we can expect higher growth rate of new infection cases in areas, where contact ban was installed.

However, first of all, we need to address the endogeneity issue. When we analyse the effect of the contact ban on the spread of SARS-CoV-2, we need to make sure that the former is not a response to the latter. The decisions on contact bans were taken at the level of Bundeslaender governments. Of course, we do not call the actions by state governments random, but we provide evidence that they were not a result of high number of new infections in a respective Bundesland. We argue that measures taken by governments were mostly preventive or driven by political disagreements with the central government, so there is no reverse causality problem. For example, the Free State of Saxony introduced the contact ban and had only 4256 registered cases per 4 mil. population by 30th April 2020. In contrast, Baden-Wuerttemberg did not experience the contact ban, but had 27,607 cases per 11 mil. of inhabitants on the same date according to the data from RKI.

Fig. 5 shows that an average daily incidence at early stages of the epidemic was even a bit lower in the Bundeslaender that have introduced the full contact ban at some point. However, the gap has narrowed by the end of the study period.

To provide more formal evidence, we estimate a linear probability model to evaluate the effect of the number of registered cases on the introduction of particular measures of social distancing. Results of these regressions presented in Table 8 demonstrate no significant relationship between the number of infections and introduction of the contact ban. Moreover, this result is robust to inclusion and exclusion of Bundesland fixed effects, implying that controlling for

![Fig. 5. Daily incidence of COVID-19 for Bundeslaender with and without contact ban.](image)

Table 8
Social distancing measures and individual mobility.

| Dependent variable: | Contact ban installed |
|---------------------|-----------------------|
|                     | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
| New cases that day  | 0.00037 | 0.00039 | 0.00027 | 0.00988 | 0.01142 | −0.00035 |
|                     | (0.00023) | (0.00025) | (0.00017) | (0.00644) | (0.00727) | (0.00143) |
| Total cases until date (’000) | 0.028 | 0.028 | 0.028 | 0.028 | 0.028 | 0.028 |
| Date FE             | No   | Yes  | Yes  | No   | Yes  | Yes  |
| Bundesland FE       | No   | No   | Yes  | No   | No   | Yes  |
| Adj. R-squared      | 0.228 | 0.234 | 0.246 | 0.140 | 0.176 | 0.000 |
| N of Bundeslaender   | 16   | 16   | 16   | 16   | 16   | 16   |
| N obs.              | 752  | 752  | 752  | 752  | 752  | 752  |

LPM regressions include a constant term. Data are from RKI and Steinmetz et al. (2020). Standard errors clustered at the Bundesland level in parentheses.

* p < 0.10.
*** p < 0.05.
**** p < 0.01.
Table 9
Effect of temperature under contact ban.

| Dep. variable: | FE       | SAR      | SDM      |
|               | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| p             |     |     |     |     |     |     |     |     |     |

| Direct effects |     |     |     |     |     |     |     |     |     |
| Contact ban    | 0.072*** | 0.070** | 0.188*** | 0.052*** | 0.050** | 0.138*** | -0.024 | -0.030 | -0.056 |
| (0.015)        | (0.015) | (0.036) | (0.010) | (0.014) | (0.031) | (0.054) | (0.050) | (0.088) | (0.013) |
| Temperature    | -0.014** | -0.009** | 0.004 | -0.013*** | -0.008* | 0.004 | 0.013 | 0.007 | -0.008 |
| (0.004)        | (0.004) | (0.004) | (0.004) | (0.004) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| Temperature × CB | -0.009*** | 0.002 |     | -0.007*** | 0.002 |     | 0.002 |     | 0.005 |
| (0.002)        |     |     |     | (0.002) |     |     |     |     |     |

| Total effects  |     |     |     |     |     |     |     |     |     |
| Contact ban    | 0.070*** | 0.068*** | 0.180*** | 0.084*** | 0.082*** | 0.220*** |     |     |     |
| (0.012)        | (0.018) | (0.042) | (0.020) | (0.020) | (0.046) |     |     |     |     |
| Temperature    | -0.014*** | -0.010* | -0.014* | -0.014* | -0.010 |     |     |     |     |
| (0.005)        | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) |     |     |     |     |
| Temperature × CB | -0.009*** | -0.011*** |     |     |     |     |     |     |     |
| (0.002)        |     |     |     |     |     |     |     |     |     |

| Between R-squared | 0.873 | 0.874 | 0.874 | 0.001 | 0.287 | 0.230 | 0.004 | 0.281 | 0.201 |
| N of obs.       | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 |

Temperature measure employed is a past weighted daily maximum. All regressions include a constant term, date and Landkreis fixed effects. SAR and SDM models use contiguity weighting matrix. Data are from RKI, CFSR and Steinmetz et al. (2020). Standard errors clustered at the Landkreis level in parentheses.

* p < 0.10.
** p < 0.05.
*** p < 0.01.

such characteristics as demography of the population or political attitudes does not significantly affect this relationship.

Once we demonstrate that measures taken by the governments of federated states were not a direct response to the epidemiological conditions they faced, we can proceed to the analysis of the effect of weather on the spread of SARS-CoV-2 under the full contact ban. Results presented in Table 9 suggest that the ban had a positive effect on the number of new cases registered. This appears a logical consequence of the fact that people have more visits to residential areas during the full contact ban. Thus, it supports the hypothesis that prohibition of social contacts in public has driven more people to private indoor areas, which facilitated transmission of SARS-CoV-2. Moreover, the magnitude of this effect is not negligible: the full contact ban increased the exponential growth rate of the number of new infections by almost 44 percent of its standard deviation. Same logic is applied to the temperature: if high values drive people outdoors, this is supposed to slow down the progress of the infection. Importantly, the negative effect of temperature is observed both under and absent the contact ban. However, the effect is significantly stronger in magnitude when the contact ban was installed. Notably, a 5-degree increase in the daily temperature can potentially offset more than 30 percent of the detrimental effect of the ban.

The relationship between weather, government regulation and the spread of the disease described above is easy to explain, if we think of taking a walk and meeting a friend during the contact ban as two competing activities. When the weather is “good”, staying outdoor is relatively more attractive and it is much easier to avoid indoor environments even if this implies being alone. As a result, “good” weather during the contact ban makes it comparatively easier to avoid social contacts, what results in a slower spread of the disease. Absent the contact ban you can still meet your friends both indoors and outdoors. However, even if “good” weather facilitates contacts, it encourages people to go outside, thus, making social interactions safer, so the overall effect is negative. These compounded relationships highlight the importance of understanding and acknowledging the weather-induced behavioural patterns. For example, it could well be that the full contact ban is an intervention with high utility costs and adverse net effects. However, its overall impact appears to be substantially reduced by a long established behavioural pattern: going out more when the weather is “good”. This is an example of a rather accidental, but, nevertheless, beneficial effect of weather-induced behaviour. Further utilising these patterns can help to develop an policy that minimises risks of infection with less utility costs.

7. Conclusion

This paper attempts to analyse the effect of human behaviour on the spread of SARS-CoV-2. For this reason we refer to weather observations that are supposed to affect the number and types of social contacts. We have identified that past weather observations have a significant and robust effect on the exponential growth rate of the number of COVID-19 cases. Inclusion of date-fixed effects removes potential problem of simultaneous trends in both dependent and explanatory variables and allows us to argue that the effect of weather is causal. Results are robust to the use of various weather characteristics (temperature, rain, humidity, heat flux). Finally, significance of temperature coefficients only at noon supports the hypothesis that this effect is primarily coming through human behaviour and not natural factors.

Moreover, we have analysed how weather affects types of places, where people interact. We find evidence that high temperature attracts more people to parks, where contagiousness of SARS-CoV-2 is expected to be lower than in indoor environments. This effect is significantly smaller during the full contact ban, but nevertheless positive. Besides that, we provide evidence that the contact ban prevents visits to parks and promotes visits to residential areas. We find a negative effect of temperatures on visits to residential areas, but most likely it comes through the visits to parks that act as a substitute activity.
Finally, we demonstrate that regions where the contact ban was imposed, benefited from high temperatures significantly more. At the same time, the contact ban resulted in higher growth rate of infections. We provide evidence that this was an exogenously imposed preventive measure and not a response to the actual epidemiologic conditions, so we can argue about causality. This is another important finding of the paper: banning contacts in public can decrease their number, but not stop them completely. Furthermore, prohibiting contacts in public can drive them indoors, thus, making them more dangerous.

Identifying the effect of behaviour on the spread of SARS-CoV-2 is important for better policy aiming to tackle the advance of infections. We believe that social distancing was the key to prevent a more severe outbreak of COVID-19. However, we still argue that there was a place for some “fine tuning” of the policies introduced by the German government. Blom et al. (2020) provide evidence that people could not cancel all social contacts. However, social interactions vary in their infection potential. Results presented in this article suggest that a policy more favourable to outdoor contacts and more prohibitive towards indoor contacts would slow down the spread of the disease even more with a smaller loss in utility. These findings are important for efficient combating of the SARS-CoV-2 during the “second wave” of epidemic that we are currently experiencing.

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**Conflict of interest**

There is no conflict of interest to declare.

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**Appendix A**

| Variable | Mean | Std. dev. | Min | Max |
|----------|------|-----------|-----|-----|
| **Panel A: Landkreis-level variables** | | | | |
| \( \gamma(t) \) & 0.392 & 0.431 & 0.000668 & 4.949 |
| Past number of infections & 224.158 & 386.232 & 0.014189 & 5786.354 |
| Past max temperature & 13.448 & 4.187 & 4.351 & 22.123 |
| Past temperature_{0.00} & 3.011 & 2.615 & -4.791 & 9.007 |
| Past temperature_{0.00} & 4.032 & 2.860 & -2.791 & 11.069 |
| Past temperature_{0.00} & 13.142 & 4.196 & 4.237 & 22.123 |
| Past temperature_{0.00} & 6.027 & 3.136 & -2.815 & 13.713 |
| Past rain & 0.441 & 0.252 & 0.013 & 0.940 |
| Past humidity & 24.771 & 8.271 & 13.573 & 48.335 |
| Past heat flux & 5606 & 22.562 & -58.626 & 66183 |
| **Panel B: Bundesland-level variables** | | | | |
| \( \Delta \text{visits to residential areas} \) & 10.564 & 6.982 & -1 & 32 |
| \( \Delta \text{visits to parks} \) & 27356 & 32.664 & -72 & 134 |
| Contact ban & 0.159 & 0.366 & 0 & 1 |
| Contact restrictions & 0.648 & 0.478 & 0 & 1 |
| 1.5 m distance & 0.700 & 0.460 & 0 & 1 |
| Prohibition to leave home & 0.214 & 0.410 & 0 & 1 |
| Daycare facilities closed & 0.752 & 0.432 & 0 & 1 |
| Schools closed & 0.748 & 0.434 & 0 & 1 |

**Table A2**

Correlation between temperature records at various times.

| Time of past temperature record: | 00:00 | 06:00 | 12:00 | 18:00 |
|----------------------------------|-------|-------|-------|-------|
| Past temperature_{0.00}         | 1     |       |       |       |
| Past temperature_{0.00}         | 0.8079| 1.0000|       |       |
| Past temperature_{0.00}         | 0.4829| 0.7839| 1.0000|       |
| Past temperature_{0.00}         | 0.7286| 0.8285| 0.7891| 1.0000|
Table A3
Alternative weather measures and changes in personal mobility.

| Dependent variable: | Δ parks | | | Δ places of residence |
|---------------------|---------|------|------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Contact ban | -13.68*** | -13.532*** | -11.955*** | -12.246*** | 1.751*** | 1.739*** | 1.714*** | 1.730*** |
| rain_{12m} | 3.499 | (2.716) | | | | | | |
| rain_{18m} | -9.747*** | (2.595) | | | | | | |
| humidity_{12m} | -1.000*** | (0.107) | | | | | | |
| humidity_{18m} | -0.733*** | (0.110) | | | | | | |
| Within R-squared | 0.018 | 0.032 | 0.122 | 0.070 | 0.062 | 0.058 | 0.079 | 0.058 |
| N of obs. | 944 | 960 | 944 | 960 | 944 | 960 | 944 | 960 |

FE regressions. Temperature measure employed is an average daily maximum. All regressions include a constant term, Bundesland and date fixed effects. Data are from Google and CFSR. Robust standard errors in parentheses.

**, p < 0.10; *** p < 0.05.
*, p < 0.01.

Fig. A1. Residual scattergram. Residuals are obtained after regressing both variables on the full set of fixed effects.

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