Corona and the Cross: Religious Affiliation, Church Bans, and Covid Infections*

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Abstract. We examine the effectiveness of church service bans in containing the spread of Covid-19 in Germany. We furthermore investigate how differences in the local religious affiliations affect infections and the effectiveness of church bans and other church-related restrictions. We find that, without a ban, infections per capita are higher in districts (Landkreise) with larger shares of religious population. In panel analysis, controlling for district fixed effects and a host of potential confounders, we find that church bans effectively reduce infections. For a ban in place for 14 days before a considered day, the predicted growth factor of infections is lower by 0.9 of its standard deviation. Finally, we show that Easter contributed significantly to the growth of infections in 2020 and 2021. The growth factor of infections was lower in regions with larger shares of Catholics and Protestants during Easter 2020 (when a church ban was in place) but not in 2021 (without a ban).

Keywords: COVID-19, infections, social distancing, religious service bans, religious affiliations.

JEL: I12, I18, R12, Z12.

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1. Introduction

The COVID-19 pandemic has caused social and economic disruption around the world. It has also produced a wealth of scientific studies from various disciplines examining the transmission of the coronavirus and measures to prevent infection and contain the spread of the disease. In this study, we focus on a topic of disease transmission that received much attention in the media but has rarely been addressed in scientific research. We study the influence of the religious composition of the population on infections at the local level and the efficacy of church bans (as well as milder forms of social distancing during religious practice) on the transmission of the disease.

The corona virus spreads mainly between people who are in close contact with each other for a sufficiently long period of time such that aerosols or droplets exhaled by an infected person are inhaled by another person (or come directly into contact with the person's eyes, nose, or mouth). Naturally, the risk of infection increases in the number of encounters and measures of social distancing were crucial in the fight against COVID-19, in particular, in the early phase of the pandemic when other preventive measures such as face masks or vaccinations were unavailable.

After the onset of the disease, it quickly became clear that church parishes were particularly conducive to the spread of the virus and potentially create "super spreader events". In church, the worshippers are in close contact with one another for long periods of time in closed rooms. Religious expressions such as praying and singing together further increase the spread of aerosols and the spread of the disease. Governments around the world responded to this potential threat by closing churches and other places of collective worshipping. In Germany, a country-wide service ban was in place from mid March to early May 2020. After the churches reopened, social distancing measures at church services were in place and their concrete design was decentralized and often determined by local governments, church governing bodies, or local church authorities.[1]

For several reasons, we expect that the efficacy of service bans and measures of infection prevention in church depend on the composition of the local population and the expression of their religiosity. Germany is a largely secularized country. More than 40 percent of the population are non-denominational and 27 percent and 24 percent of the population belong to the Catholic and Protestant churches (FOWID, 2021a). Only a few members of these "Large Churches"

[1]In this study, for the sake of linguistic simplicity, we use the term church as a generic term for all public places of collective worship and common prayer.

(Großkirchen) attend service weekly or more than weekly. There is, however, substantial variation across denominations and across districts. Among Protestants, 3.2 percent attend church weekly or more than weekly. Among Catholics, this number rises to 9.1 percent (FOWID, 2021b). The distribution of denominations across Germany and even within its federal states is very uneven in international comparison, a feature that goes back to the Peace of Augsburg (1555), the religious freedom granted by Frederick the Great (1740), and the fact that Germany never had a state religion. As a result, the dominant local denomination is largely predetermined by the personal preferences and political agenda of the local rulers in place prior to the foundation of the German Empire (1871).

In light of these stylized facts, we would expect that when churches are open, ceteris paribus, infections spread more easily in predominantly Catholic districts because attendance rates are relatively high. For this reason, one might also expect that church bans will be more effective in predominantly Catholic regions. The efficacy of a ban, however, depends on the unobserved change in behavior when gatherings at church are prevented. For example, people may respond by worshipping alone or within the family at home, by increasing secular Sunday activities, or by relocating collective worshipping to private places.

Several Christian minorities in Germany, such as the New Apostolic Church, Jehovah's Witnesses, or Baptists, are jointly addressed as Evangelical Free Churches (Evangelische Freikirchen, average population share around 1 percent). Their average attendance rate is much higher than for Catholics and Protestants, around 50 percent (FOWID, 2018). This behavior is consistent with Iannaccone's (1988, 1992) economic theory of church and sect, which explains why members of small religious denominations benefit more from collective worship and are particularly interested in maintaining high attendance. The same logic applies to attendance rates among Orthodox Christians and Muslims. The latter comprise the largest of the "Other Non-Christian" affiliations.[2] Members of these groups are largely not only religious minorities but also ethnic minorities in Germany, with migration background from the Balkans and CIS countries or MENA countries, respectively. It can be assumed that their religious gatherings fulfill additional functions such as the exchange of information and the preservation of cultural identity. A strong motive for religious minorities to meet together can undermine the social distancing

[2]According to FOWID (2019), already in 1986 there were 1.6 million Muslim people in Germany, while in 2011 around 2.1 million identified themselves as affiliated with "other" religions (including Islam).

effect of church bans, as groups meet anyway and, in response to the ban, gatherings take place in smaller private rooms with high population densities.

After the general church ban was lifted at the beginning of May 2020, services were possible again under locally applicable restrictions, depending on the local rate of new infections. Restrictions included the requirement to wear face masks, distance rules, limited attendance, and a ban on singing together. The new rules created a new way by which religiosity could play a role for infections in addition to church attendance, namely compliance. Religiosity may reduce compliance because of religiously motivated beliefs (e.g. that the virus would not hit "the righteous") or because of limited cognitive reflection and low trust in science. The latter view is supported by studies in cognitive psychology distinguishing between cognitive ability as the capacity to engage in analytical reasoning and cognitive style as the willingness or disposition to engage in analytical reasoning (e.g. Stanovich and West, 1998). While cognitive ability is largely given for adults, cognitive style is a choice, i.e. a problem could be tackled either in a fast, intuitive-believing style or a slow reflective-analytic style (Kahneman, 2011; Evans, 2008). It has been found that low performance in so called cognitive reflection tests is a strong predictor of religiosity (Shenhav et al., 2012; Gervais and Norenzayan, 2012). Strulik (2016) proposes an economic theory of religiosity based on cognitive style.

The tradeoff between religious belief and scientific attitude is also observed in society at large. Using the World Value Surveys, Benabou et al. (2015) document a strong association between alternative measures of religiosity and negative attitudes toward science (e.g. the view that there is too much dependence on science versus faith). If there exists a religiously motivated underestimation of infection risk, it may become apparent after the resolution of the church ban in form of higher infection rates in districts with a larger proportion of (strictly) religious believers. Anecdotal evidence for the compliance channel is provided by the German press, which reported on several COVID-19 mass outbreaks caused by the failure to observe restrictions at services, with a disproportionate proportion of the outbreaks occurring in congregations of the Evangelical Free Churches (e.g. FAZ, 2020; Spiegel, 2020; TAZ, 2020).

Mass outbreaks of COVID-19 in churches and the phenomenon of non-compliance with corona restrictions at church gatherings were observed not only in Germany but around the world, see e.g. Quadri (2020); Wildman et al. (2020); The New York Times (2020). Results from the Cooperative Election Study showed that 8 percent of the U.S. Americans who said they attended church more than weekly also reported a COVID-19 infection while the rate of infection among those who attended seldom (less than yearly) was 4 percent (Burge, 2021). However, as acknowledged by Burge, infections are self-reported and thus biased and identifying a causal channel is difficult because both church attendance and reported infections may be driven by a common cause.[3] Vermeer and Kregting (2020) observed for the Netherlands that most of the municipalities severely affected by COVID-19 were located in highly religious areas known as the Dutch Bible belt. They found that both church membership and attendance played a role in the spread of the disease and concluded that religion likely helped spread the disease directly through religious services, but also indirectly through cultural festivals such as carnival. Bentzen (2021) showed that Google searches for prayer increased substantially during the Covid-19 pandemic, reflecting the intensified demand for religion during crisis. We contribute to this literature and to the general literature on social distancing during the Covid pandemic by showing in panel regressions the effect of church bans and other restrictions on the spread of the disease within local populations, stratified by religious denomination.

The remainder of the paper is organized as follows. Section 2 describes the data and our empirical strategy. Section 3 presents the results. We first investigate the relationship between the religious composition of the local population and infections during the first wave of the pandemic (when a church ban was in place) and the second and third wave (without a church ban). We then turn to panel estimates of within-region effects of church bans and other church restrictions on the growth factor (the R value) of local infections. Controlling for a host of other confounders, we also investigate how the efficacy of church bans and restrictions is channeled through the religious composition of the local population. Finally, we compare the impact of Easter 2020 (when a church ban was in place) and Easter 2021 (without a ban) on the growth factor of infections in regressions whereby we control for Bundesland-date fixed effects, i.e. for any potentially time-varying effects of policy measures at the Bundesland level. Section 4 concludes the paper.

[3] We believe that misreporting is not a serious concern in the case of Germany where the ratio of deaths (which is difficult to under-report) to recorded cases was lower than in most other countries (Lau et al., 2021). In our sample, the correlation coefficient between the total number of registered cases and deaths was 0.78, implying that the two figures are tightly linked with each other. Nevertheless, we have also repeated our analysis for deaths and found very similar patterns to registered cases (see Table 10 in the Appendix).

2. Data and Empirical Strategy

2.1. **Data.** We use data on religious affiliations at the NUTS-3 level provided by the last round of the German Census in 2011. Respondents were asked to indicate their affiliation with one of the seven religious groups: Catholics, Protestants, Free Evangelicals, Orthodox Christians, Jewish, and Other Religion. Alternatively, respondents could claim no religious affiliation (Census, 2011). Because Jews are a very small minority, absent from 90 percent of regions, we conflate this religious group with "Other Religions" for compactness. The fact that more recent data on religious affiliation at the regional level are not available causes no problem because affiliations change only very gradually. The only exception could be the category "Other Religion", which we believe to be primarily Muslim. According to FOWID (2021a), in 2020 there were 5.5 million Muslims (6.5 percent of total population), out of which 2.9 million were active believers. Thus, we argue that changes in relative sizes of communities affiliated with "other religion" were still minor compared to the two dominant religions: Catholics and Protestants. Moreover, the migration literature argues that existing diasporas are likely to attract new immigrants to the same areas (Beine et al., 2011, 2015). Thus, sizeable communities affiliated with "other religions" today are likely to remain in the same regions as in 2011.

We use data on daily COVID infections provided by Robert Koch Institute (2021). This is the government's central scientific institution in the field of biomedicine responsible for identification, surveillance and prevention of diseases, especially infectious diseases. To start with, we consider per capita incidence of COVID-19 cases in the German NUTS-3 regions (*"Landkreise"*).[4] Each case registered has two dates: infection and registration. If it is known to the health ministry, when the infection took place, this date is used. Otherwise, the registration date is used. The date of infection is available for 71 percent of cases in our sample. This feature limits potential concerns about delayed or irregular reporting.

Given that the spread of the disease was not monotonic and to account for numerous time-variant factors that could affect the progress of the number of infections (e.g., distancing policies, adaptation of population, weather) we divided the study period into three waves, as shown in Figure 1. We define Wave I as the period from the beginning of the epidemic to June 1, 2020. Then the number of new infections was low until around October 1 and we refer to it as a period of relatively low incidence. Skyrocketing of the COVID-19 cases marked the beginning of

[4] All analysis presented in this paper was conducted at the Landkreis level.

Wave II, which we consider to last from October 1, 2021 until the start of Wave III on March 1, 2021. The third wave lasted until June 1, 2021, when our study period ends. The division in waves allows us to analyze effects of particular factors in comparable settings. For example, daily incidence during wave I was much lower than during wave II, when the virus was already more evenly distributed across the country.

[Figure 1 about here.]

2.2. **Religious Affiliation and Incidence of Infections: Cross-Sectional Regressions.** In this paper, we aim to analyze the effect of religiosity on the spread of COVID-19 in a broad perspective. First, to analyze the effect of religious affiliation of the local population on the spread of COVID-19 we ran a set of cross-sectional regressions:

$$z_i = \beta X_i + \gamma C_i + \epsilon_i. \tag{1}$$

In these regressions, the dependent variable z_i is the share of population of a Landkreis i who were infected with SARS-CoV-2 according to RKI data during the respective wave. A vector X_i=$\{$*Catholic*$_i$*, Protestant*$_i$*, Free Evangelic*$_i$*, Orthodox*$_i$*, other*$_i\}$ includes the shares of the population affiliated with a particular religion – this is the set of our main explanatory variables of interest. We chose unaffiliated as the reference group. We employ a wide set of socio-demographic indicators, that potentially could affect the spread of the disease: population size, per-capita income, shares of population above 65 and below 29 years old, the share of females, the shares of population with an academic degree and without professional education, and, following Krenz and Strulik (2021), regional road accessibility. These data were sourced from INKAR (2021). Finally, we also include the share of population with migration background, as migrants can have different socializing patterns and, at the same time, practice only particular religions. These figures are obtained from the results of the German Census in 2011. The variables are collected in a vector of control variables C_i=$\{$*ln(population*$_i$*), per capita GDP*$_i$*, accessibility*$_i$*, population 29-*$_i$*, population 65+*$_i$*, population w/o degree*$_i$*, population w degree*$_i$*, share of females*$_i$*, share of migrants*$_i\}$. The majority of social distancing measures were introduced by the governments of the federal states (*"Bundesland"*). In order to control for effects of these measures we also include Bundesland fixed effects. This reduces the number of regions from 401 to 399, as Berlin and Hamburg are federal states with only one region.[5]

Besides considering only religious affiliation of the population, we also analyze efficiency of church closures and restrictions of religious services. At the beginning of the epidemic, when little was known about the disease, the governments introduced very strict lockdown measures. One of the widespread policies was a ban on all religious services in the country. Figure 2 demonstrates that a church ban was rapidly (but not simultaneously) installed in all federal states and was in place for approximately one month. Afterwards, single states were replacing the full ban with various restrictions, such as limiting the number of attendants or prohibiting singing during the service, but the complete ban was never introduced again.

As church-related restrictions were not the only measures aiming to slow down the spread of COVID-19, we also need to control for the effect of not religion-related measures. Initially, all measures introduced by the government are binary variables taking a value of 1 if the measure was in act in a given region on a particular day. However, given that we do not know, when exactly a person was infected, we calculate *probabilities* that a person was infected when a particular measure was in act using a weighting procedure described below. In short, a value of 1 implies that we are confident that the contagion took place, when a measure was in act, and 0 implies that we are confident that the measure was not in act when the contagion took place. Data on timing of particular measures are provided by Steinmetz et al. (2020).

[Figure 2 about here.]

A potential concern could be that governmental measures were introduced as a consequence of a high number of infection cases registered in a region. However, we argue that this was not the case, as the general government has acknowledged the threat of the disease before the takeoff of infections and the majority of measures were thus of preventive nature. In support of this claim, we found that there exists no significant relationship between a church ban or other restrictions and new cases or total cases registered on the day before the measure was introduced. As lead time of one day might be considered too short, we also considered an interim time frame that could influence the local governments' decision to impose bans or restrictions: one and four weeks. The results of these regressions are shown in Table 5 in the Appendix and demonstrate

[5] Berlin city districts are de-jure separate regions, however they belong to a single urban area, thus, we merge their values and consider them as one big region throughout the whole study.

no significant association between past infections and imposition of particular measures. In our regressions, we included time-fixed effects to control for the general perception of the situation with the virus in the world. In any case, note that if there were reverse causality (i.e., higher incidence forces the government to introduce the ban), our estimates would indicate the lower bound of the infection-reducing effect of bans and restrictions.

2.3. **Church Bans and the Spread of Infection within Regions: Panel Estimates.** To examine the effect of religious affiliation on the efficacy of church bans (and other policies) in containing the spread of infections, we need to evaluate an average contagiousness in the region for every single day of the study period. That is why we cannot rely on a simple daily incidence. To illustrate this claim, consider two examples. In region A, 10 infection cases identified on day $t-7$ create 15 new infections identified on day t. In region B, 100 infection cases identified on day $t-7$ create 50 new infections identified on day t. If we rely on a simple incidence, region B will appear more heavily affected with the disease, but we also see that the infection progresses faster in region A implying that containment measures are less efficient there. Secondly, we face substantial heterogeneity across regions: while some regions can be hot spots of the epidemic, others remain relatively safe. For example, if on a given day no infections were registered, it does not necessarily mean that there were no single infection transmission a week before. To solve these two issues, we estimate an effective reproduction number R, that is the number of new infection cases generated, on average, by one infected person. The use of the R value allows us to evaluate the efficiency of infection containing policies.

To estimate R, we use a simple deterministic SEIR (susceptible, exposed, infectious, recovered) model. This is a type of compartmental model that is used for mathematical modeling of infectious diseases. The Appendix contains a formal description of the theoretical model. Given that individuals infected with SARS-CoV-2 can be contagious without symptoms for a certain period of time, we select the model that explicitly considers exposed individuals. This is not a novel approach in epidemiology of respiratory infections. For example, Mills, Robins and Lipsitch (2004) use a SEIR model to study transmissibility of the 1918 influenza pandemic, while studies by Prem et al. (2020) and Chang et al. (2021) employed the methodology for COVID-19 analyses.

The estimation of R is associated with a set of issues. First of all, for any reported infection case, we do not know when exactly the person was infected. We thus operate with *probabilities* that the contagion took place on a particular day. Existing studies of SARS-CoV-2 suggest that the incubation period of the infection does not exceed 14 days and in most infection cases lasts 6-7 days (Backer et al., 2020). We assume that individuals diagnosed with COVID-19 on day t were *not* infected in $t-15$ or earlier and employ the distribution function of the length of incubation periods estimated by Backer et al. (2020). We apply it to calculate the *expected* number of contagious individuals in a region that could transmit SARS-CoV-2 to individuals diagnosed on day t. In other words, we estimate how many people got infected on average by one person, which is the estimated daily growth factor of the disease. The disease expands for $R > 1$ and declines for $R < 1$. The logarithm of the growth factor provides the growth rate of the disease.

The growth factor of the disease R is our dependent variable in the panel regressions. The regression equation takes the following form:

$$R_{it} = \beta_1 m_{it} + \beta_2 m_{it} X_i + \beta_3 G_{it} + \eta_i + \varepsilon_{it}, \tag{2}$$

where m_{it} is a weighted average value of the past government measures to contain the spread of SARS-CoV-2 (either full ban or restriction of religious services) in a region i and day t. Analogously to R, we weight binary variables indicating whether a respective measure was in act in a region on each day between $t-14$ and $t-1$ using the distribution of incubation periods by Backer et al. (2020). The resulting measure can also be interpreted as a probability that infections registered today took place when a particular ban or a restriction was in act in that region. In order to compare the efficacy of the ban and restriction, we conduct this analysis only during wave I, when both measures were in act at some point. In later waves a full ban on religious services was not introduced. X_i is a vector of shares of local population affiliating themselves with a particular religious group. The matrix G_{it} contains a set of time-variant control variables. First, we include past temperature, as it could significantly affect the modality and hence contagiousness of human interactions (Yakubenko, 2021). Then, to isolate the effect of the ban on religious services, we also include the major other social distancing measures to isolate the effect of the ban on religious services: minimum distance of 1.5 meter to other persons, closure of non-essential shops, and a restriction on private gatherings of more than five people. All social distancing measures were also weighted, as described above, and can be read as probabilities that people diagnosed today were infected when a particular policy was in act.

We also need to account for demographic factors. First, we expect that elderly people are more likely to be more religious. At the same time, elderly people can have different socializing patterns or self-isolate more, as the virus was particularly dangerous for them. Thus, the share of the population that identifies as Catholic can potentially pick up the effect of the region's age composition. We have therefore included the share or population older than 65 as an important control alongside with religious shares. Secondly, we follow a similar logic in case of people with migration background since church attendance allows migrants to maintain closer connections in their communities.

Finally, regional fixed effects η_i capture the time-invariant characteristics of the regions (*Landkreise*), such as demography and infrastructure. For example, Rader et al. (2020) demonstrate that size and density in agglomerations can significantly affect the spread of COVID-19.

The interaction term between anti-COVID measures and the shares of the regional population affiliated with a particular religion $m_{it}X_i$ allows us to exploit two sources of variation. First, we analyze the share of a potential incubation period that coincides with a particular event such as the presence of a ban on religious services. Second, we include the share of religious population that is expected to be more affected by the church ban. It is plausible to expect that people who do not associate themselves with a particular religion also do not attend religious services and will experience no direct effects from church bans or restrictions. It is possible, however, that the unaffiliated benefit indirectly from church bans and restrictions because they are confronted with fewer infected people in their environment. Nevertheless, if the population share of unaffiliated people is large, the practical effect of a church ban is expected to be small, which means that we expect the effect of a ban on religious services to be greater in regions with more religious people. In other words, the interaction term $m_{it}X_i$ can be read as the share of the local population that was *directly* affected by a ban or restrictions of services of a particular religious group.

3. Results

3.1. **Religious Affiliation and Infections at the Local Level.** Results of our first round of cross-sectional regressions described by equation (1) are presented in Table 1. We see a small positive association between the share of Catholics and the number of infections during Wave I, which might be explained by the Carnival celebrations that coincided with the arrival of SARS-CoV-2 in Germany, before any restrictions were imposed. Otherwise we hardly see any influence of religious affiliation on the spread of COVID-19 during Wave I, i.e. in the period when the church ban was in place. In the waves II and III, in contrast, we generally observe a positive association between religious affiliation of the population and infections per capita. The size and statistical significance of the effect varies across religions and waves.

As can be seen from Figure 2, the whole country experienced a church ban only during Wave I, so during Waves II and III people were allowed to attend church in some restricted form. This can potentially explain why we see a positive and significant effect of religious affiliation on infections per capita during the later waves. The results suggest that Landkreise with more religious people suffered a higher incidence of COVID-19. We observe some heterogeneity between religions in terms of the magnitudes of the effects. The association between religious affiliation and infections is larger for Catholic share than for Protestant share and it is particularly large for the share of Free Evangelicals and those affiliated with other religions. The former is consistent with the anecdotal evidence mentioned in the Introduction.

[Table 1 about here.]

The regression coefficients of the control variables in Table 1 appear intuitive. We see no significant association with income – even in column (3) the magnitude of the coefficient is negligible. As in Krenz and Strulik (2021), lower accessibility is associated with a lower spread of infections. The same holds for the share of population below age 30: young individuals typically have lower incidence and severity of COVID-19 due to a number of biological features (Zimmermann and Curtis, 2021). As a result, young people have both lower levels of infections and are less likely to develop severe symptoms, which means that they may not require testing. The share of the elderly population has no significant association with infection rates. Although being more vulnerable, the elderly were more likely to isolate themselves and were among the first to be vaccinated. Furthermore, the share of working population with no professional education positively affects incidence, while workers with an academic degree have the opposite effect. This result serves as another example for the central importance of education. The coefficient for the share of females in the population is mostly insignificant, an observation in line with Peckham et al. (2020) who argue that there is no difference between the proportion of males and females with COVID-19 infections. Finally, we see a significantly positive effect of the share of population with migration background on per capita infections, suggesting that higher cohesion within communities of migrants could play an unfavorable role during the epidemic.

Table 1 provides the results for the number of infections. Even though there is evidence that Germany was efficient in detecting infections (Lau et al., 2021), we still need to provide evidence that religious affiliation was not a significant factor for misreporting of the infection status. For this reason, we have also conducted our analysis using the number of deaths as a dependent variable. As deaths are arguably hard to misreport, we expect that they can serve as a proxy for the analysis of the true number of infections. The disadvantage of this indicator is that it shows the time of death and not infection, while we are primarily interested in determining when the contagion actually took place. However, when we aggregate the number of deaths across waves, this drawback is mitigated to some extent. Table 10 provides results that demonstrate similar relationship between religious affiliation and the number of recorded deaths. The only exception is the absence of a significant association with the share of Free Evangelicals and other Christians, which is explained by the fact that we had too few deaths recorded to see any significant effect for these minority groups.

Results presented above suggest that religion had an effect on COVID-19 incidence. Moreover, we see some empirical evidence for the efficiency of church bans. We found no significant association between religion and incidence of COVID-19 in wave I, when religious services were banned for a substantial share of the period. In contrast, when services were allowed in some form, religious affiliations became significant correlates of infections per capita. However, from these results we cannot convincingly argue that the effects presented come solely from changes in church-related politics. For example, religious people could be more compliant with other policies. Alternatively, the change in coefficients could still be explained in a number of ways such as weather influences or changing perceptions of the threat of infection. These problems are addressed by the subsequent panel analysis. We focus first on wave I, as it was the only period when the governments of the federal states introduced a complete ban on religious services. Thus, we can easily compare the impact of this measure across regions and religious groups. Additionally, we analyze the effect of restrictions of religious services to see whether there was any difference between religious groups.

3.2. **Religious Affiliation and Restrictions of Religious Services: Panel Regressions.** The results from panel regressions of equation (2) are presented in Table 2. To be able to compare the effects of the ban and restrictions, we consider only wave I, when both measures were introduced at some point.[6]

The results in column (1) show that both the ban and restrictions of religious services were associated with a slower spread of SARS-CoV-2. We observe a sizeable effect of the ban and restrictions: if the measure was in act 14 days before the considered day, we expect R to be lower by 0.9 and 0.8 standard deviations, respectively. Having auxiliary controls included, we can also be certain that these effects are not driven by weather fluctuations or some other social-distancing measures.

[Table 2 about here.]

A ban on religious services will not affect everyone equally. For example, we expect stronger effects of church bans for religions with higher attendance rates. Thus, it is important to consider the religious composition of the local population. To capture these heterogenous effects, we allow the coefficient of the ban to vary across religious affiliations. As the reference group we take again the unaffiliated because we expect regions with relatively more unaffiliated people to be less affected by a church ban, as the unaffiliated typically do not attend church.

The results presented in columns (2) and (3) of Table 2 suggest the ban and restrictions on religious services are especially pronounced in regions populated with more Catholics. This effect is robust to the inclusion of the share of elderly population and people with migration background, as seen in column (3). We find several potential explanations to the fact that the ban and restrictions are especially efficient in Landkreise with more Catholics. First of all, Catholics are the largest religious group in Germany presented in all regions of the country (FOWID, 2021a). Secondly, as mentioned above, the attendance rate of Catholics is much higher than that of Protestants, the second largest religious group. It has to be noted that even though Free Evangelic churches typically have higher attendance, the number of affiliated people is much smaller, as can be seen in Table 4. In other words, in absolute numbers Catholics have much more regular attendees. For example, we also observe infection reducing effects of the ban and restrictions in regions populated with more Orthodox, but quantitatively these effects are moderate, if we factor in the sizes of the Orthodox communities (on average 1 percent of the population and never more than 6.5 percent). Interestingly, the higher share of Free Evangelicals

[6] As a robustness check we have also considered ban and restrictions separately. These results are presented in Table 6. in the Appendix.

is not associated with a slower spread of infections during the ban and restrictions of religious services. We have two potential explanations for this outcome. First, the population share of Free Evangelicals may be too small for church bans to have a statistically significant effect. Second, as was mentioned above, Free Evangelicals may comply less with the regulations than other religious groups.

It should be noted that our results suggest that church bans and restrictions have a positive impact on all regions, regardless of their religious composition. This appears to be a plausible result: even if people do not generally attend church (like the unaffiliated or a large proportion of Protestants), they can still benefit from the infection containing measures through a safer environment in their Landkreis.

Another remarkable result is the large positive coefficient for other religions in column (2). To calculate the overall effect of the ban, however, we need to factor in the small share of the population affiliated with other religions. In our sample it is equal to 0.023. We ran a one-sided t-test with the null-hypothesis assuming that $\beta_{ban} + \beta_{ban \times other} \cdot 0.023 < 0$ and obtained a p-value of 0.988. As for restrictions, a similar exercise also returned a p-value of 0.988. Thus, we argue that even though the share of population affiliated with other religions reduced the effectiveness of the containment measures, the overall effect of the ban and restrictions was still significantly negative. In this case, however, it is difficult to distinguish between religion and a minority status, as people not affiliated with traditionally German religions are likely to have migration background. In the case of migrants, church attendance can in particular be driven by non-religious motives such as obtaining information or maintaining social cohesion. Thus, when places of worshipping are closed, people socialize somewhere else and presumably in private places with higher population densities and greater risks of infection. This statement is supported by the results presented in column (3), where the significant effect of other religions disappears, when we include the share of migrants into the regression.

3.3. **Religious Holidays and Spread of COVID-19: Panel Regressions.** So far, we have provided evidence that bans and restrictions of religious services can reduce the number of potentially contagious social contacts. We observed significant effects of these measures although Germans do not attend religious services very often: on average, only 9 and 3 percent of the officially affiliated believers regularly attend Catholic and Protestant churches (FOWID, 2021). However, church attendance varies substantially throughout the year and, in particular, during the major religious holidays attendance rates are significantly higher (Liturgische Konferenz, 2019). The increased load on places of worshiping makes it harder to follow social distancing measures on holidays. To check whether this feature is visible in the data, we next consider a major religious holiday in Germany: Easter (12th April 2020 and 4th April 2021) and explore its impact on infections.[7]

An added benefit of having another source of variation is that we can control for a substantial share of unobservable factors by including Bundesland-date fixed effects. With Bundesland-date fixed effects we take into account that many measures aiming at containing the spread of COVID-19 were introduced at the Bundesland level and we address potentially time-variant effects such as changing perceptions of the threat of infection or the adaptation of the population to the installed measures. In other words, Bundesland-date fixed effects absorb effects of all possible policy interventions in place in a federal state on a particular day.

Additionally, we account for the feature that Easter could take place at different phases of the infection waves. To that end, we include pre-Easter infection trends in form of past R values in the regression, which capture whether the number of new infections was on the rise or decreasing. As with governmental measures, we construct a weighted average value of R during the incubation period of infections diagnosed on day t. The resulting variable indicates the average contagiousness of contacts during the period, when a person was infected.

Despite the fact that our fixed effect setting absorbs all policy effects, we are still able to compare efficiency of bans and restrictions of religious services. For this purpose, we run our exercise separately for waves I and III. We know that all religious services were banned during Easter 2020 and allowed but restricted in 2021. This means our results show the difference of Easter infections (compared to a normal day) when church attendance is prohibited vs. when church attendance is allowed.

Considering the waves separately reduces the degree of heteroscedasticity, as during wave I COVID-19 has spread from several individuals across the whole country, while during wave III the virus was already more evenly distributed across the population. Another important reason to conduct the exercise separately for two waves is the possible existence of different variants of the virus in wave I and wave III. By separating the waves, we compare Easter with non-Easter days of the same wave, when the same variant was prevalent. As a robustness check, we have

[7] We cannot investigate time changes of the “holiday impact” for Christmas because it occurred only once since the beginning of the epidemic in Germany until the end of our study.

also conducted the regression for a joint sample of waves I and III and obtained similar results (see Table 7).

It has to be noted that, besides being an important religious event, Easter also brings two public holidays - Easter Friday and Monday. Thus, we can expect all religious affiliations and the unaffiliated to be affected by it, albeit presumably in different ways. While Catholics, Protestants and Free Evangelicals have an explicit reason to celebrate (both in church or privately), all other groups face an extended weekend with no important religious holidays. For this reason, we merge unaffiliated, Orthodox, and others into one big reference group and compare them with Catholics, Protestants, and Free Evangelicals. The Easter variable can be read as the probability that cases registered on day t were infected during Easter. Our sample spans from March till June in both years.

[Table 3 about here.]

Results of these regressions are presented in Table 3. The results from columns (1) and (3) demonstrate that Easter contributed to the spread of SARS-CoV-2 in Germany differently, when church services were banned and allowed. In wave I we find no significant association between Easter and the spread of COVID-19. Wheras in wave III the magnitude of the holiday effect was more than three standard deviations of R. These results are not surprising, as it has been shown that the modality of human interactions plays a huge role in the dynamics of the epidemic (Yakubenko, 2021).

Besides the sheer effect of Easter, we are interested in its heterogeneity between regions populated with different religious groups. Here, we found that the holiday effects differ substantially across waves and religious groups. These differences can be explained by the nature of the different policies that were in act during the two periods. For the first wave, we observe in column (2) of Table 3 a significant negative effect of Easter in regions inhabited by more Catholics and Protestants. It is important to remember that during Easter 2020, all religious services in Germany were prohibited, so the observed effect cannot be attributed to organized church services. First of all, the coefficients of Easter for Catholics and Protestants can simply capture the effect of a church ban that was in place during Easter 2020. In contrast, people affiliated with other religions, who do not celebrate Easter, did not need to change their weekend routine nor limit the scope of their contacts.

This interpretation of results is corroborated when we consider wave III. As shown in column (4) of Table 3, results change substantially compared to Wave I. We now find no significant differences of the Easter effect between different religions. An obvious reason for this outcome is the change in contagion policy: church services were restricted but nevertheless allowed. Apparently, Easter celebrations involving a church visit did not differ much to other activities: individuals have contact with people who they do not meet regularly and with complete strangers. As a result, the population share of Catholics and Protestants affect infections on Easter when churches are closed but not when churches are open.

4. Conclusion

In this paper, we investigated church bans as one particular method of social distancing and demonstrated the efficacy of the measure in terms of reduced infections. Using COVID-19 infections data for the 401 German Landkreise, we first showed that the local population share of Catholics, Free Evangelicals, and other religious affiliations contributed significantly to the spread of the disease during the second and third wave of the pandemic (when there was no church ban) but not during the first wave (when a ban was in place). In waves without a church ban, we found a particularly large effect on infections for the share of Free Evangelicals. The evidence supports the view that churches as places of public gathering are particularly conducive to the spread of diseases.

We then computed the daily local growth factor (the R value) of the disease and showed in panel analysis, controlling for district fixed effects and a host of potential confounders, that church bans effectively reduce infections. For a ban in place for 14 days before a considered day, we predict the growth factor of infections to be lower by 0.9 of its standard deviation. We also demonstrated the efficacy of other restrictions in containing the disease spread in church.

Finally, we compared infections caused on Easter 2020 and 2021 and found a sharp contrast between them. We argued that the primary source of this difference are the policies that were in act during Easter over the two years. When religious services were allowed during Easter 2021, the population share of Catholics or Protestants played no role in the spread of infections. The evidence thus suggests that church visits during Easter 2021 (when they can be considered a mass phenomenon) were not different in their contagious potential to secular activities that people undertake during holidays. When religious services were banned during Easter 2020, however, we found a significantly lower growth factor of infections in regions with large shares of Catholics and Protestants.

Overall, our results confirm the finding of related studies showing the importance of social distancing in containing the spread of Covid-19. More specifically, our results corroborate the scientific and anecdotal literature arguing that religious gatherings have promoted the spread of infection during the COVID-19 pandemic. Our study suggests that imposing restrictions on church services has helped contain the spread of the virus in Germany.

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Appendix

The Model. To analyze the dynamics of the epidemics we refer to a simple SEIR model. Under the standard formulation the model consist of as a set of differential equations that describe evolution of susceptible, exposed, infectious and recovered populations. As we are primarily interested in the analysis of contagiousness we focus on the infected individuals and assume the share of susceptible individuals to be equal to 1. We believe that this assumption is reasonable in our setting. For analysis of the efficacy of the ban and restrictions of religious services, we use data from Wave I (until 1 June, 2020). By this time in total 182 thousand cases of COVID-19 were registered in Germany, what is roughly equal to 0.2 percent of the total population. 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).

The evolution of a number of cases diagnosed with the disease is:

$$\alpha \dot{I} = (1-\alpha) I r(t) \gamma + \alpha I r \gamma_h - (1-\alpha)\frac{I}{\gamma} - \alpha \frac{I}{\gamma_h}. \tag{A1}$$

I is the total size of the currently infected population and α is the share of infected with revealed symptoms. We assume that only symptomatic cases (αI) were registered, but asymptomatic cases ($(1-\alpha)I$) are contagious and an infected individual generates r new cases while she or he is contagious. γ is the mean communicability period for asymptomatic cases and γ_h is the mean time from infection to isolation of individuals with symptoms – the incubation period. The last two characters in Eq.A1 stand for recovery of asymptomatic and isolation of symptomatic individuals, respectively.

We rearrange Eq. A1 as:

$$\alpha \dot{I} = I\lambda, \quad \text{where} \quad \lambda \equiv \frac{r(t)\left((1-\alpha)\gamma^2\gamma_h + \alpha\gamma\gamma_h^2\right) - (1-\alpha)\gamma_h - \alpha\gamma}{\gamma\gamma_h}. \tag{A2}$$

Assuming α to be constant, the solution to Eq. A1 is:

$$\alpha I(t) = \alpha I(0) e^{y(t)}, \quad \text{where} \quad y(t) \equiv \int \lambda(t) dt, \tag{A3}$$

and $I(0)$ is the initial number of infected. $y(t)$ is the average growth rate of infection cases over an incubation period. As Eq.A2 and A3 demonstrate, besides the probability of infection that we expect to vary daily during the communicability period, $y(t)$ also accounts for the duration of communicability and the fact that not everyone develops symptoms despite being contagious.

As it is now, $y(t)$ represents an average growth rate of infection cases from the beginning of the epidemic until day t. However, in our study we want to follow evolution of contagiousness under the influence of particular factors, such as changes in policy. Thus, we focus on weighted 14-days intervals - incubation periods - and follow evolution of cases not from the first day of the epidemic, but from the first day of the incubation period of infections diagnosed by a doctor on day t. To avoid breaks in the data on days, when there were no infections registered, we calculate our average exponential growth rate of new infections over the incubation period by adding 1 to the number of infections. Putting both sides of the Eq.A3 in natural logarithms and rearranging it yields us:

$$\hat{y}(t) = \ln(I(t) + 1) - \ln(I^p(t) + 1), \tag{A4}$$

where $\ln(I^p(t))$ is an average number of infections diagnosed and recorded by RKI between $t-1$ and $t-14$ weighted using the distribution derived by Backer et al. (2020). Now $\hat{y}(t)$ is the *estimated* average growth rate of the number of infection cases diagnosed on day t over the incubation period. However, for an easier interpretation of our results, we can refer to Eq.A3 and use the fact that $e^{y(t)}$ can be read as the number of new infections generated from the initial number of infections until day t. Given that we fix the time frame equal to one incubation period, we can obtain the *effective* reproductive number:

$$R(t) = e^{\hat{y}(t)}. \tag{A5}$$

In other words, $R(t)$ tells us how many new infections an average infected person diagnosed with COVID-19 and isolated from the population on day t was generating while being contagious.

[Table 4 about here.]

[Table 5 about here.]

[Table 6 about here.]

[Table 7 about here.]

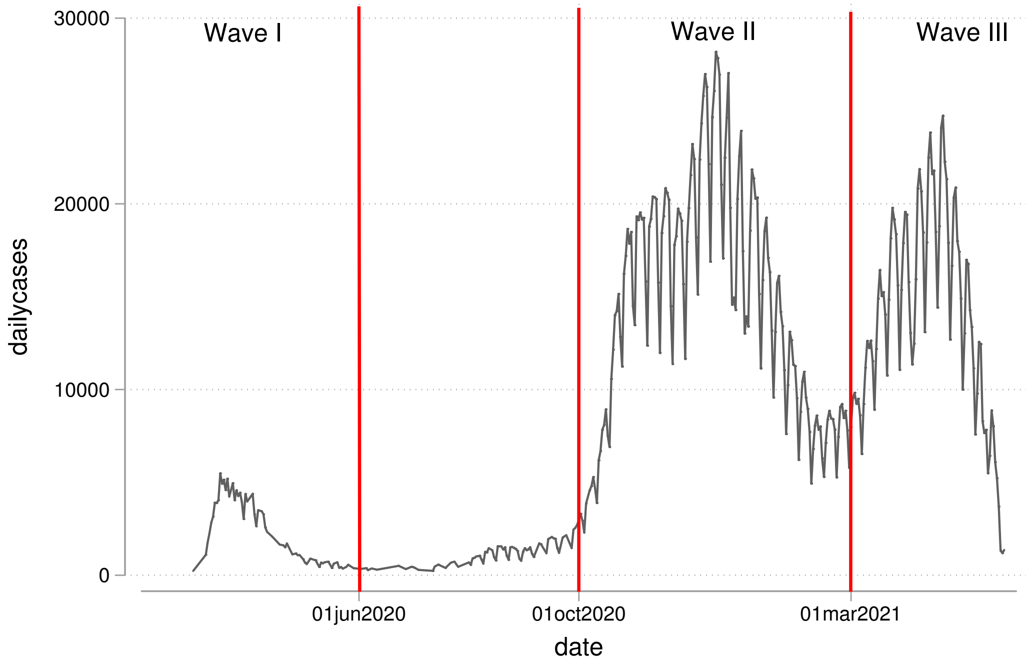
[Table 8 about here.]

[Table 9 about here.]

[Table 10 about here.]

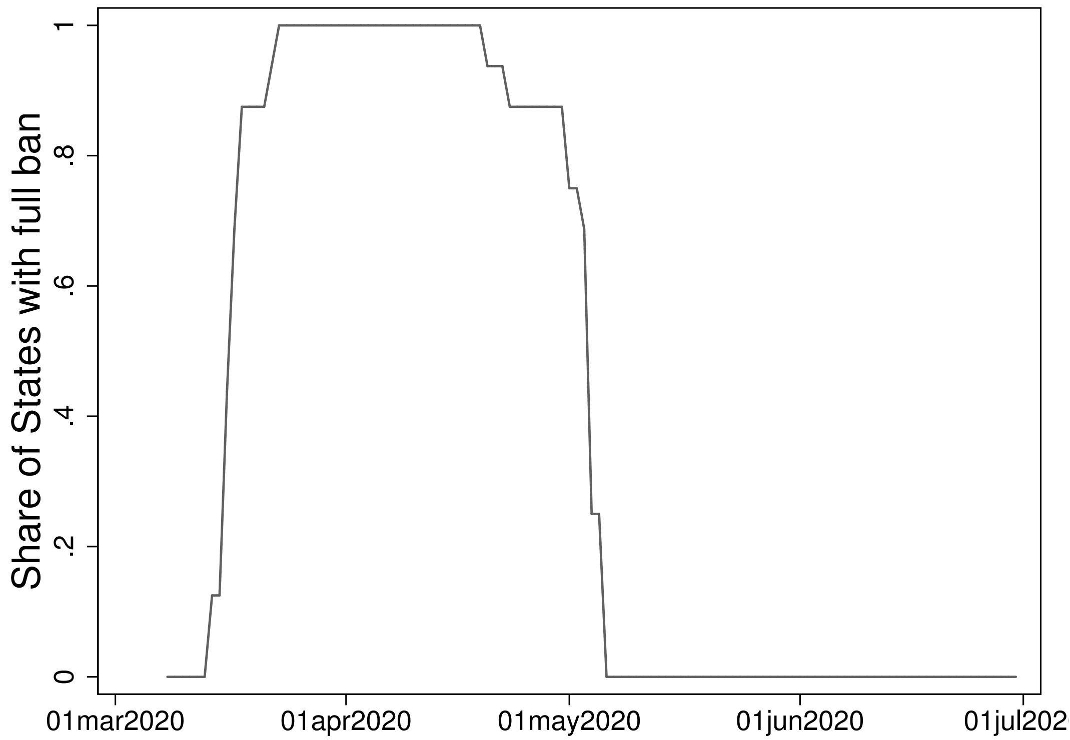
[Table 11 about here.]

Figure 1. Daily National Incidence of COVID-19



Source: RKI (2021)

Figure 2. Share of Federate States with Church Ban



Source: Steinmetz et al. (2020).

Table 1. Per Capita Incidence of COVID-19.

Dep. variable:	infections per capita				
Wave:	I	II	III	II & III	All
	(1)	(2)	(3)	(4)	(5)
Catholic	0.002*	0.026***	0.006	0.032***	0.034***
	(0.001)	(0.008)	(0.006)	(0.012)	(0.012)
Protestant	0.001	0.022***	0.007	0.029**	0.029**
	(0.001)	(0.008)	(0.006)	(0.012)	(0.013)
Free Evangelic	0.007	0.067	0.064**	0.131**	0.132**
	(0.008)	(0.046)	(0.028)	(0.060)	(0.063)
other	0.000	0.058	0.067***	0.124**	0.133**
	(0.011)	(0.042)	(0.025)	(0.056)	(0.059)
Orthodox	0.013	-0.047	0.033	-0.015	0.004
	(0.014)	(0.061)	(0.043)	(0.084)	(0.091)
ln(population)	0.000	0.001	0.001	0.002*	0.002*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
GDP_{pc}	0.000	-0.001**	0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
accessibility	-0.001	-0.007**	-0.006***	-0.013***	-0.014***
	(0.001)	(0.003)	(0.002)	(0.004)	(0.004)
share 29-	-0.006	-0.090***	-0.038*	-0.127***	-0.136***
	(0.007)	(0.034)	(0.020)	(0.046)	(0.046)
share 65+	-0.003	-0.031	-0.017	-0.048	-0.057
	(0.005)	(0.033)	(0.018)	(0.044)	(0.045)
share w/o degree	0.002	0.012	0.024	0.036	0.041
	(0.008)	(0.032)	(0.021)	(0.044)	(0.045)
share w degree	-0.000	-0.026**	-0.035***	-0.062***	-0.063***
	(0.002)	(0.010)	(0.006)	(0.014)	(0.014)
share female	0.009	0.108*	-0.032	0.076	0.078
	(0.014)	(0.059)	(0.037)	(0.079)	(0.081)
share migrants	-0.003	0.061***	0.013	0.073***	0.073***
	(0.003)	(0.013)	(0.010)	(0.020)	(0.021)
N	399	399	399	399	399
Adj. R-squared	0.368	0.597	0.574	0.663	0.655

OLS regressions. All regressions include Bundesland FE and a constant term. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2. Governmental Measures and Religious Affiliation: Panel Regressions

Dep. variable:	$R(t)$		
	(1)	(2)	(3)
ban	-0.655***	-0.385***	-1.158***
	(0.079)	(0.089)	(0.370)
restrictions	-0.586***	-0.433***	-1.035***
	(0.077)	(0.093)	(0.371)
ban×Catholic		-1.084***	-0.992***
		(0.132)	(0.156)
ban×Protestant		-0.328*	-0.310
		(0.186)	(0.195)
ban×Free Evangelic		3.134	2.924
		(3.918)	(4.065)
ban×Orthodox		-7.805*	-11.105*
		(4.330)	(6.263)
ban×other		7.004***	3.055
		(2.624)	(3.548)
ban×share 65+			3.140**
			(1.463)
ban×share migrants			1.180
			(0.803)
restrictions×Catholic		-0.880***	-0.846***
		(0.130)	(0.154)
restrictions×Protestant		-0.164	-0.173
		(0.202)	(0.209)
restrictions×Free Evangelic		4.327	3.535
		(3.800)	(4.035)
restrictions×Orthodox		-6.866	-11.895*
		(4.544)	(6.977)
restrictions×other		6.184**	1.512
		(2.754)	(3.576)
restrictions×share 65+			2.436
			(1.479)
restrictions×share migrants			1.432
			(0.889)
past temperature	-0.023***	-0.022***	-0.022***
	(0.002)	(0.002)	(0.002)
1.5 metre distance	-0.270***	-0.199***	-0.196***
	(0.062)	(0.057)	(0.056)
shops closure	-0.112***	-0.098***	-0.099***
	(0.023)	(0.023)	(0.023)
private gatherings	0.216***	0.218***	0.221***
	(0.034)	(0.034)	(0.033)
Landkreis FE	Yes	Yes	Yes
mean $R(t)$	0.990	0.990	0.990
SD $R(t)$	0.737	0.737	0.737
N	31278	31278	31278
Number of regions	401	401	401
Adj. R-squared	0.127	0.137	0.137

FE regressions. Unaffiliated are the omitted category in columns (2) and (3). Standard errors clustered at the Landkreis level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Easter and Spread of COVID-19: Panel Regressions

Dep. variable:	R(t)			
Wave:	I		III	
	(1)	(2)	(3)	(4)
past R	-0.118***	-0.143***	0.266***	-0.069***
	(0.022)	(0.024)	(0.019)	(0.018)
Easter	0.245		1.876***	
	(0.182)		(0.088)	
Easter × Catholic		-5.411***		-0.756
		(1.473)		(1.034)
Easter × Protestant		-3.804**		0.103
		(1.874)		(1.254)
Easter × Free Evangelical		-5.085		-9.843
		(17.569)		(15.846)
past temperature	-0.015***	-0.009	-0.043***	0.002
	(0.002)	(0.010)	(0.001)	(0.006)
Landkreis FE	Yes	Yes	Yes	Yes
Bundesland × date FE	No	Yes	No	Yes
mean $R(t)$	0.899	0.899	0.983	0.983
SD $R(t)$	0.640	0.641	0.506	0.507
N	25664	25536	34887	34713
Number of regions	401	399	401	399
Adj. R-squared	0.013	0.040	0.162	0.364

OLS regressions. The baseline category includes unaffiliated, Orthodox and others. Column (1) includes past measures of social distancing. Standard errors clustered at the Landkreis level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Summary statistics of used variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: cross-sectional variables					
cases per capita (wave I)	399	0.002204	0.0016541	0.0003011	0.0156681
cases per capita (wave II)	399	0.0257026	0.009272	0.0056667	0.0624468
cases per capita (wave III)	399	0.0145733	0.005444	0.0034591	0.0412494
cases per capita (waves II&III)	399	0.0402758	0.0134526	0.0091257	0.0901965
cases per capita (all waves)	399	0.043651	0.0139895	0.0104472	0.0928824
share of Catholics	399	0.3352353	0.2488237	0.0191933	0.887439
share of Protestants	399	0.3167559	0.1750839	0.0454727	0.7588371
share of Free Evangelicals	399	0.0075983	0.0081158	0	0.0621516
share of Orthodox	399	0.0107221	0.0092562	0	0.0645703
share of other religions	399	0.0225975	0 .0146717	0	0.0957371
ln(population)	399	11.96711	0.6309765	10.44024	14.2018
GDP_{pc}	399	3.561412	1.587353	1.59209	17.87063
accessibility	399	0.2267669	0.1599366	0	0.69
share 65+	399	0.209948	0.0234753	0.1510057	0.2821923
share 29-	399	0.3024633	0.0285184	0.221618	0.3866958
share w/o degree	399	0.0914463	0.0704263	0.0087515	0.4720327
share w degree	399	0.0953563	0.0732854	0.016784	0.4460912
share females	399	0.5057835	0.0063432	0.4872	0.5249
share migrants	399	0.1673506	0.0947615	0.0181919	0.4972176
Panel B: panel variables					
R (wave I)	31,278	0.990247	0.7371988	0.0352052	20.45963
R (wave III)	34,887	0.982866	0.506134	0.004058	5.585498
church ban	31,278	0.5969858	0.4529527	0	1
church restrictions	31,278	0.2885	0.4281776	0	1
1.5 metre distance	31,278	0.8488997	0.3319456	0	1
shop closure	31,278	0.4666617	0.4621128	0	1
private gatherings	31,278	0.8210393	0.3589873	0	1
past temeprature	31,278	15.02278	4.089088	4.324472	23.45356

Table 5. Past infections and governmental measures

Dep. variable:	church ban							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
new cases yesterday ('000)	0.00355	0.00001						
	(0.01050)	(0.02781)						
total cases ('000)			0.00024	0.00011				
			(0.00037)	(0.00045)				
total cases last week('000)					0.00075	0.00246		
					(0.00154)	(0.00448)		
total cases last 4 weeks('000)							0.00044	0.00110
							(0.00065)	(0.00109)
N	109874	109874	109874	109874	107468	107468	99047	99047
Number of regions	401	401	401	401	401	401	401	401
Adj. R-squared	0.938	0.939	0.938	0.939	0.938	0.939	0.945	0.947
Dep. variable:	restrictions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
new cases yesterday ('000)	0.10131	0.12875						
	(0.14532)	(0.31274)						
total cases ('000)			0.00062	0.00043				
			(0.00046)	(0.00282)				
total cases last week('000)					0.01653	0.02242		
					(0.02223)	(0.05654)		
total cases last 4 weeks('000)							0.00427	0.00640
							(0.00461)	(0.01821)
N	180847	180847	180847	180847	178441	178441	170020	170020
Number of regions	401	401	401	401	401	401	401	401
Adj. R-squared	0.780	0.843	0.780	0.843	0.778	0.842	0.773	0.843

LPM regressions. Odd columns include Date fixed effects, even columns include both Date and Bundesland fixed effects. Standard errors clustered at the Bundesland level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Governmental Measures and Religious Affiliation: Panel Regressions

Dep. variable:	$R(t)$			
	(1)	(2)	(3)	(4)
ban	-0.130***	-0.015		
	(0.023)	(0.038)		
ban×Catholic		-0.343***		
		(0.057)		
ban×Protestant		-0.122		
		(0.081)		
ban×Free Evangelic		-1.164		
		(1.539)		
ban×Orthodox		-2.216		
		(1.868)		
ban×other		2.902***		
		(1.083)		
restrictions			-0.049**	-0.119***
			(0.021)	(0.040)
restrictions×Catholic				0.040
				(0.053)
restrictions×Protestant				0.160*
				(0.091)
restrictions×Free Evangelic				1.840
				(1.468)
restrictions×Orthodox				-0.019
				(1.986)
restrictions×other				-0.362
				(1.159)
past temperature	-0.025***	-0.025***	-0.024***	-0.024***
	(0.002)	(0.002)	(0.002)	(0.002)
1.5 metre distance	-0.589***	-0.601***	-0.593***	-0.595***
	(0.044)	(0.044)	(0.042)	(0.043)
shops closure	-0.129***	-0.122***	-0.262***	-0.262***
	(0.023)	(0.022)	(0.020)	(0.020)
private gatherings	0.143***	0.156***	0.147***	0.148***
	(0.035)	(0.035)	(0.036)	(0.036)
Landkreis FE	Yes	Yes	Yes	Yes
mean $R(t)$	0.990	0.990	0.990	0.990
SD $R(t)$	0.737	0.737	0.737	0.737
N	31278	31278	31278	31278
Number of regions	401	401	401	401
Adj. R-squared	0.116	0.118	0.114	0.114

OLS regressions. Unaffilaited are the omitted category in columns (2) and (4). Standard errors clustered at the Landkreis level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Easter and Spread of COVID-19: Joint Sample

Dep. variable:	R(t)	
	(1)	(2)
past R	0.105***	-0.089***
	(0.016)	(0.017)
Easter	1.326***	
	(0.177)	
Wave III	-0.007	
	(0.009)	
Easter×Wave III	0.563***	
	(0.206)	
Easter 2020×Catholic		-4.112***
		(1.353)
Easter 2021×Catholic		-1.634
		(1.037)
Easter 2020× Protestant		-2.132
		(1.692)
Easter 2021× Protestant		-1.080
		(1.271)
Easter 2020× Free Evangelic		-13.610
		(15.969)
Easter 2021× Free Evangelic		-4.339
		(15.149)
past temperature	-0.039***	0.000
	(0.001)	(0.005)
Landkreis FE	Yes	Yes
Bundesland × date FE	No	Yes
N	60150	59850
Number of regions	401	399
Adj. R-squared	0.071	0.194

OLS regressions. The baseline category includes unaffiliated, Orthodox and others. Column (1) includes past measures of social distancing. Standard errors clustered at the Landkreis level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 8. Governmental Measures and Religious Affiliation: Bundesland-level SEs

Dep. variable:	R(t)	
	(1)	(2)
ban	-0.655**	-0.385
	(0.268)	(0.222)
restrictions	-0.586**	-0.433*
	(0.268)	(0.221)
ban×Catholic		-1.084***
		(0.191)
ban×Protestant		-0.328
		(0.302)
ban×Free Evangelic		3.134
		(5.146)
ban×Orthodox		-7.805
		(6.780)
ban×other		7.004
		(4.161)
restrictions×Catholic		-0.880***
		(0.190)
restrictions×Protestant		-0.164
		(0.417)
restrictions×Free Evangelic		4.327
		(5.437)
restrictions×Orthodox		-6.866
		(6.192)
restrictions×other		6.184
		(4.250)
past temperature	-0.023***	-0.022***
	(0.003)	(0.002)
1.5 metre distance	-0.270	-0.199
	(0.203)	(0.165)
shops closure	-0.112***	-0.098***
	(0.028)	(0.025)
private gatherings	0.216***	0.218***
	(0.062)	(0.049)
N	31278	31278
Number of regions	401	401
Adj. R-squared	0.127	0.137

OLS regressions. Unaffiliated are the omitted category. Standard errors clustered at the Bundesland level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Easter and Spread of COVID-19: Bundesland-level SEs

Dep. variable:	R(t)			
Wave:	I		III	
	(1)	(2)	(3)	(4)
past R	-0.118***	-0.143***	0.266***	-0.069***
	(0.027)	(0.030)	(0.046)	(0.016)
Easter	0.245		1.876***	
	(0.221)		(0.126)	
Easter× Catholic		-5.411*		-0.756
		(2.552)		(1.707)
Easter× Protestant		-3.804		0.103
		(2.398)		(2.050)
Easter× Free Evangelic		-5.085		-9.843
		(23.878)		(11.384)
past temperature	-0.015***	-0.009	-0.043***	0.002
	(0.002)	(0.018)	(0.004)	(0.005)
Landkreis FE	Yes	Yes	Yes	Yes
Bundesland × date FE	No	Yes	No	Yes
mean $R(t)$	0.899	0.899	0.983	0.983
SD $R(t)$	0.640	0.641	0.506	0.507
N	25664	25536	34887	34713
Number of regions	401	399	401	399
Adj. R-squared	0.013	0.040	0.162	0.364

OLS regressions. The baseline category includes unaffiliated, Orthodox and others. Column (1) includes past measures of social distancing. Standard errors clustered at the Bundesland level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10. Deaths of COVID-19.

Dep. variable:	deaths per 1000 inhabitants				
Wave:	I	II	III	II & III	All
	(1)	(2)	(3)	(4)	(5)
Catholic	0.270*	0.887**	0.222*	1.109**	0.001***
	(0.138)	(0.450)	(0.120)	(0.475)	(0.000)
Protestant	0.165	1.139**	0.229*	1.368**	0.002***
	(0.120)	(0.505)	(0.137)	(0.532)	(0.001)
Free Evangelic	0.763	-1.800	0.481	-1.318	-0.001
	(0.920)	(3.031)	(0.758)	(3.146)	(0.003)
other	-1.037	0.170	0.319	0.489	-0.000
	(1.157)	(2.765)	(0.649)	(3.004)	(0.003)
Orthodox	1.374	-4.239	-0.558	-4.797	-0.003
	(1.348)	(3.735)	(1.033)	(3.917)	(0.004)
ln(population)	0.008	-0.038	0.006	-0.033	-0.000
	(0.018)	(0.054)	(0.010)	(0.055)	(0.000)
GDP_{pc}	0.013*	-0.035**	0.003	-0.032*	-0.000
	(0.007)	(0.017)	(0.004)	(0.018)	(0.000)
accessibility	-0.142**	-0.258	-0.085*	-0.343**	-0.000***
	(0.072)	(0.162)	(0.043)	(0.174)	(0.000)
share 29-	-0.462	-5.468***	-1.212**	-6.680***	-0.007***
	(0.920)	(1.954)	(0.521)	(2.069)	(0.002)
share 65+	0.423	-0.173	0.378	0.205	0.001
	(0.544)	(2.018)	(0.458)	(2.194)	(0.002)
share w/o degree	0.781	1.112	0.248	1.359	0.002
	(0.945)	(1.705)	(0.471)	(1.799)	(0.002)
share w degree	-0.229	-0.274	-0.345*	-0.619	-0.001
	(0.274)	(0.641)	(0.182)	(0.669)	(0.001)
share female	1.103	2.684	0.626	3.311	0.004
	(1.613)	(3.329)	(0.994)	(3.620)	(0.004)
share migrants	-0.305	2.511***	0.322	2.833***	0.003***
	(0.311)	(0.826)	(0.250)	(0.899)	(0.001)
N	399	399	399	399	399
Adj. R-squared	0.198	0.495	0.467	0.564	0.533

OLS regressions. All regressions include Bundesland FE and a constant term. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 11. Correlation matrix of used variables

	Catholic	Protestant	Free Evangelic	other	Orthodox	ln(population)	ln(GDP)	accessibility	share 25-	share 65+	share w/o degree	share w/degree	share female	share migrants
Catholic	1.0000													
Protestant	-0.5140***	1.0000												
Free Evangelic	-0.2350***	0.4036***	1.0000											
other	0.1281**	0.1375***	0.2295***	1.0000										
Orthodox	0.2012***	-0.0168	0.0995**	0.7158***	1.0000									
ln(population)	-0.0602	-0.0460	0.2406***	0.3212***	0.2503***	1.0000								
ln(GDP)	0.1384***	-0.0696	-0.0239	0.4096***	0.5637***	0.0725	1.0000							
accessibility***	-0.1409***	0.1760***	0.1465***	-0.4235***	-0.4811***	-0.1287***	-0.4753***	1.0000						
share 25-	0.4905***	0.0060	0.1440**	0.4386***	0.4938***	0.1884***	0.4058***	-0.3612***	1.0000					
share 65+	-0.5299***	0.0918**	-0.0782	-0.2922***	-0.3859***	-0.2618***	-0.2257***	0.1708***	-0.8277***	1.0000				
share w/o degree	0.4282***	0.2243***	0.1997***	0.7054***	0.6167***	0.0867	0.3214***	-0.2806***	0.6439***	-0.4749***	1.0000			
share w/degree	-0.0890	-0.1577**	-0.0591	0.2990***	0.4715***	0.3694***	0.5351***	-0.5515***	0.3768***	-0.2314***	0.0123	1.0000		
share females	-0.2845***	0.1198**	-0.0137	0.1259**	0.0580	0.0642	0.0244	-0.2656***	-0.2054***	0.3764***	-0.0467	0.3235***	1.0000	
share migrants	0.2819***	0.0880	0.2465***	0.8639***	0.8522***	0.2649***	0.5819***	-0.4874***	0.604***0	-0.4392***	0.8188***	0.3859***	0.0753	1.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$