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The socio-economic determinants of COVID-19: A spatial analysis of German county level data

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ABSTRACT

The study explores the association of socioeconomic, demographic, and health-related variables at the regional level with COVID-19 related cases and deaths in Germany during the so-called first wave through mid-June 2020. Multivariate spatial models include the 401 counties in Germany to account for regional interrelations and possible spillover effects. The case and death numbers are, for example, significantly positively associated with early cases from the beginning of the epidemic, the average age, the population density and the share of people employed in elderly care. By contrast, they are significantly negatively associated with the share of school-children and children in day care as well as physician density. In addition, significant spillover effects on the case numbers of neighbouring regions were identified for certain variables, with a different sign than the overall effects, giving rise to further future analyses of the regional mechanisms of action of COVID-19 infection. The results complement the knowledge about COVID-19 infection beyond the clinical risk factors discussed so far by a socio-economic perspective at the ecological level.

1. Introduction

Since its outbreak in December 2019 in Wuhan Province, China, the respiratory disease COVID-19 has developed in just a few weeks into a pandemic with currently (12 February 2021) about 107 million infections and about 2.4 million deaths worldwide. Many countries have responded with one or more successive lockdowns (including curfews and school closures), in particular to avoid overloading the health system. The initial exponential growth in case numbers has now slowed in many countries or, in many cases, resulted in multiple separate waves of infection.

In Germany the first confirmed cases were reported at the end of January 2020. The number of new infections per day rose to more than 100 at the beginning of March 2020 and reached a preliminary maximum of about 7000 at the end of March 2020 (what defined the peak of the first wave). The initial cases were mainly attributed to imported clusters spread at major events (e.g. sports, carnival).

The social and economic consequences of the lockdown measures taken in almost all countries to contain the pandemic are serious and their long-term development is not yet foreseeable. Currently, with the exception of a few flagship countries or regions, there is still no general vaccination (worldwide approx. 160 million vaccinated, 12.02.2021) and thus no effective herd immunity. This increases the pressure for empirical evaluation of prevailing contact restrictions and, hence, for the development and implementation of targeted and efficient future political measures. While clinical and epidemiological research is currently discussing person-specific risk factors for infection or probability of survival, which often have a strong ad hoc influence on government lockdown measures, there are so far few results on the question of which socio-economic and region-specific factors (after controlling the initial case numbers of a region) are associated with the spread of COVID-19 at an ecological level.

In order to understand the ecological study approach chosen here and to distinguish it quite clearly from (clinical) studies based on individual data, the following should be emphasized: This study’s units of analysis are groups (401 German counties) with the corresponding data aggregated at the group level. Hence, the conclusions derived also apply only at the group level. Therefore, no direct conclusions can be derived at the individual level (this can lead to so-called ecological fallacies). In this regard, there are numerous examples in the literature of factors having a different influence at the group level than at the individual level, see, e.g. Ref. [8] and the literature cited therein.

Nevertheless, ecological studies do have a high relevance and justification, especially around (political) measures that also refer to groups instead of individuals (as is the case with many collective COVID-19 measures). Furthermore, they serve to generate hypotheses about
possible mechanisms of action in the sense of exploratory studies before individual-level studies are even available, as is the case worldwide at the onset of the COVID-19 pandemic. To address a classic example of such mechanisms of action: It can be assumed that persons of low socio-economic status are more severely affected by COVID-19. The possible interrelationships are manifold. For example [11], highlights the coincidence of multiple (and thus mutually reinforcing) health risk factors (such as living in crowded conditions, poorer hygienic conditions, jobs that are unfavorable to health with little opportunity for home office, therefore increased use of public transport, etc.) associated with low social status. For comparable ecological studies in influenza and COVID-19, see, e.g. Refs. [1,35,40].

The current hypotheses concerning socio-economic factors influencing COVID-19 at an ecological level are manifold. For example, the average age of the population, regional vaccination rates against tuberculosis, climatic factors, or the way schools and childcare facilities are managed, have recently been discussed in the daily press in terms of their impact on the spread of COVID-19. With this ecological analysis, further socio-economic factors at the level of the 401 counties in Germany (whose infection numbers vary considerably, see Fig. 1) will be analysed with the help of spatial statistical methods.

Besides the explorative character of this analysis (at the current state of research), three questions in particular are to be answered empirically: First, what possible influence do schoolchildren and children in day care have on the occurrence of infection? Second, can the thesis of the spread of COVID-19 via institutions for care of the elderly be empirically confirmed at regional level? Third, what influence do spillover effects, i.e. the interlinked spread of COVID-19 between neighbouring regions, have on infections? Other factors which have not yet been quantitatively investigated, but which can be discussed based on the results of this study include, for example, the question of the influence of the size of the dwelling (regarding the question of frequency of contacts), tourism (supra-regional spread) or the sectoral structure (contacts in the office or on the building site).

To answer these questions, the case numbers and deaths at the district level provided for Germany by the Robert Koch-Institut (RKI) are associated with socio-economic, demographic and health-related data at the same regional level. The analysis period is Germany’s first wave of COVID-19 cases and deaths until mid-June 2020. The data are analysed by three types of spatial models, the spatial autoregressive model (SAR), the spatial error model (SEM) and the spatial autoregressive combined model (SAC). The spatial position of the regions relative to each other is represented by a weighting matrix. These models can reduce possible bias of an ordinary least squares (OLS) estimation in case of spatial spillovers and/or increase the efficiency of the estimation.

This paper complements the existing literature in at least three areas. Firstly, the literature on COVID-19 tends to focus on clinical studies to identify individual risk factors and develop curative treatments, see e.g. Ref. [43]. However, the contribution of this study lies precisely in the identification of key socio-economic and demographic factors and the possible regional mechanisms of action through which COVID-19 spreads at an ecological level. Examples from the literature on the analysis of socio-economic risk factors of health status are numerous. As a classic example [12], deals with the various, also socio-economic, determinants of individual health. For infectious diseases such as pneumonia and influenza [13], has investigated the influence of socio-economic factors in addition to individual risk. Socio-economic risk factors for HIV were analysed by Ref. [2], for pertussis by Ref. [17], for salmonella infections by Ref. [41] and for H1N1 pandemic mortality in the USA by Ref. [29], to name only some examples.

Secondly, socio-economic risk factors in relation to COVID-19 have so far been analysed rather for regions outside Germany or in an international comparison of countries. Examples are [24] for 20 European countries, which points to a positive influence of high social activity and high population density on COVID-19 infections, or [35,36] for a worldwide analysis of risk factors based on country data. Examples of regional analyses in Spain are [25], for an analysis at municipal level within Catalonia [23], for France [14], for Iran [32], for China [30], or [4] for Italy, to name a few. For the analysis at the district level within Germany [28], finds significantly negative effects especially on income and education. In a spatial regression discontinuity analysis [3] investigate the influence of the tuberculosis vaccination along the former inner-German border under consideration of numerous socio-economic factors at the district level. A time series approach taking into account regional factors such as age and population density was carried out by Ref. [22] and aims to explain the decline in infection rates in the later phase of the first COVID-19 wave.

Thirdly, however, in the above analyses (with the exception of [5]) no spatial econometric models (and hence no possibility for spatial spillover effects) have been considered. Outside Germany, similar approaches have been applied by Ref. [34] for spatial models (without spillover effects) at the European country level. For 31 regions in China [15] analyses the spatial spillover effects for the COVID-19 case numbers, but without considering socio-economic covariates.

The rest of the paper is structured as follows. Section 2 details the data and methods used. Results are presented in Section 3. Section 4 provides a discussion and concludes.

2. Methods

2.1. The data

Our analysis is a retrospective ecological study on the level of the 401 administrative districts and district-free cities (counties) in Germany, whose population ranges from about 34,000 (Zweibrücken) to about 3,664,000 (Berlin). It should be emphasized again that this is not a clinical study at the level of single individuals, so that accordingly statements can only be made at the population level. However, this study design is well established in the health sciences and provides very practice-oriented results, especially for questions in the areas of health services research, public health and epidemiology. See also [21] for a detailed discussion.

As outcome variables the case numbers and deaths at the district level, which are currently updated daily by the RKI, are used. The cut-off date for this analysis is 15. June 2020. The data are based on reports

Fig. 1. Cumulative infection numbers per 100,000 population from the start of the COVID-19 pandemic to June 15, 2020 (data source: RKI).
from the local health authorities to the RKI. As officially recorded COVID-19 cases, the figures are a lower limit of the actual number of cases present (dark figure).

The socio-economic, demographic and health-related variables at the district level come from two public sources, namely the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) and the Central Research Institute of Ambulatory Health Care in Germany (ZI). Table 1 provides an overview of the data.

In selecting the covariates, we were guided by existing ecological studies on respiratory diseases and the motivation for the relevance of the corresponding variables discussed there. For example, the influence of income and education variables as well as the region type on COVID-19 infections is discussed in [28]. While the motivation for the first two variables is widely accepted in the literature as classic determinants of health status, the region type in this context can provide further evidence on the accessibility or remoteness of a region and the associated transport flows, in addition to mere population density. Importantly, region type is classified according to the presence of cities and the proportion of the population living there, which will certainly have an impact on the spread of COVID-19 at the ecological level. For many regions in Germany, there are significant differences for this indicator compared to mere population density.1 For a motivation of the employment level on pandemic events, see e.g. [20]. Demographic variables, population density and information on health status are discussed in Ref. [3]. The physician density is brought into play in Ref. [30] in connection with COVID-19 infections in China. Note also that a very similar selection and grouping of socio-economic factors (but at the level of nation states) on COVID-19 infections is used in [35].

In general, the actual mechanisms of action behind the socio-economic factors are complex. For example, they can act simultaneously at the individual and population level and their direction is often unclear a priori. In the case of the economic status of a region, for example, the better infrastructure available to bridge a lockdown or further contact restrictions can be seen as an effect that slows down the spread of infection. The same applies to better medical treatment. On the other hand, a region’s higher economic output generally increases the networking and thus the frequency of contact between individuals, which can have an increasing effect on the number of infections. Also, with higher economic performance, more resources are available for testing for COVID-19, so that this alone can also result in a positive association.

However, some rather uncommon variables that we have included in Table 1 should be briefly motivated explicitly. In addition to the classical economic indicators, the share of academics serves as a proxy for higher education and an indication of the economic progressiveness and possibly openness of a region. The literature also pays attention to the further diffusion of knowledge among academics, which could facilitate mitigation strategies in the wake of COVID-19. On the other hand, social (cross-regional) interaction among academics may also be assumed to be higher [38], which in turn accelerates an infection event. The direction of effect is unclear a priori, leaving the academics variable all the more interesting for our analysis.

The industry share of the workforce was included as a plausible indicator for the possibility of working from a home office, which is often lacking in industry, and which would then favor the occurrence of infection. A more international perspective on the same question is answered by the immigration for humanitarian reasons variable. In addition to the mere proportion of foreigners, this variable allows a distinction to be made between highly qualified (and therefore more likely to work flexibly and online) foreigners and foreigners who are in Germany for humanitarian reasons and either perform low-skilled work (under conditions that are unfavorable from a pandemic perspective) or are often housed in collective accommodations, which also facilitate the

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1 See https://www.bbsr.bund.de for details.

### Table 1

| Indicator                  | Definition                                                                 | Year  | Mean | SD   | N    | Source |
|----------------------------|---------------------------------------------------------------------------|-------|------|------|------|--------|
| COVID-19                   |                                                                           |       |      |      |      |        |
| Case numbers               | As of 15. June 2020                                                      | 2020  | 464.99 | 656.15 | 401 | RKI    |
| Early cases                | As of 08. March 2020                                                     | 2020  | 2.63  | 15.22 | 401 | RKI    |
| Death count                | As of 15. June 2020                                                      | 2020  | 21.92 | 30.29 | 401 | RKI    |
| Economy                    |                                                                           |       |      |      |      |        |
| HH income                  | Average monthly household income in EUR per inhabitant                   | 2017  | 1872.56 | 215.76 | 401 | BBSR   |
| Unempl. rate               |                                                                           | 2017  | 5.36  | 2.41  | 401 | BBSR   |
| Pers. services             | Share of employees in personal services                                   | 2017  | 23.87 | 4.65  | 401 | BBSR   |
| Pers. nursing              | Personnel in nursing homes per 10,000 inhabitants                         | 2017  | 97.71 | 23.28 | 401 | BBSR   |
| Academics                  | Share of employed academics                                              | 2017  | 13.06 | 6.20  | 401 | BBSR   |
| Industry share             | Employees in industry per 100 working-age population                      | 2017  | 18.25 | 8.72  | 401 | BBSR   |
| Service share              | Employees in the service sector per 100 working-age population            | 2017  | 39.24 | 14.84 | 401 | BBSR   |
| Tourist beds               | Beds in tourist accommodation per 1000 inhabitants                       | 2017  | 41.78 | 49.31 | 401 | BBSR   |
| Old age pov.               | Percentage of the population with basic old-age provision in the population 65 years and older in promille | 2017  | 22.37 | 14.63 | 401 | BBSR   |
| Demography                 |                                                                           |       |      |      |      |        |
| Mean age                   |                                                                           |       |      |      |      |        |
| Over 75                    | Population 75 years and older                                            | 2017  | 44.54 | 1.96  | 401 | BBSR   |
| Women                      | Share of women                                                           | 2017  | 11.72 | 1.62  | 401 | BBSR   |
| Health                     |                                                                           |       |      |      |      |        |
| Heart failure              | Proportion of heart failure patients in relation to all patients (covered by statutory health insurance) | 2017  | 3.85  | 1.42  | 401 | ZI     |
| COPD                       | Proportion of COPD (chronic obstructive pulmonary disease) patients in relation to all patients (covered by statutory health insurance) | 2017  | 6.46  | 1.50  | 401 | ZI     |
| Physicians                 | Physicians per 10,000 inhabitants                                        | 2017  | 14.59 | 4.41  | 401 | BBSR   |
| Hospital beds              | Hospital beds per 1000 inhabitants                                        | 2016  | 6.35  | 3.89  | 401 | BBSR   |
| Pharmacies                 | Pharmacies per 100,000 inhabitants                                       | 2017  | 27.00 | 6.11  | 401 | BBSR   |
| Infant mortality           | Share of deaths under 1 year per 1000 inhabitants under 1 year            | 2017  | 3.31  | 1.76  | 401 | BBSR   |
| Life expectancy            | Persons in need of care per 10,000 inhabitants                            | 2017  | 80.66 | 1.01  | 401 | BBSR   |
| Need of care               |                                                                           | 2017  | 428.13 | 106.03 | 401 | BBSR   |
| Region                     |                                                                           |       |      |      |      |        |
| Pop. density               |                                                                           |       |      |      |      |        |
| Car density                | Cars per 1000 inhabitants                                                 | 2017  | 533.75 | 702.71 | 401 | BBSR   |
| Commuter balance           | Comuter balance (in minus out) per 100 employees subject to social insurance at the place of work | 2017  | 10.36 | 29.72 | 401 | BBSR   |
| Share of foreigners        |                                                                           | 2017  | 10.03 | 5.15  | 401 | BBSR   |
| Immigr. human. Reasons     | Proportion of humanitarian refugees in the population                     | 2017  | 1.88  | 1.14  | 401 | BBSR   |
| Multi-fam. houses          | Share of apartments in multi-family houses                                 | 2017  | 45.83 | 19.39 | 401 | BBSR   |
| Region type                | 1 – urban regions. 2 – regions with urbanisation                          | 2017  | 2.05  | 0.79  | 401 | BBSR   |

(continued on next page)
To check if the multiple indicators (especially in the health domain) do not lead to a pronounced multicollinearity in the model, we also examined the variables in Table 1 for correlations, which, however, turn out to be rather low overall. Only some variables show correlations greater than 0.8, namely physicians and service share (0.86), commuter balance and service share (0.83), and over 75 and mean age (0.92). Among the health variables, only hospital beds and physicians have a value of a similar magnitude (0.79).

### 2.2. Econometric methods

In contrast to a standard linear model, in our analysis the spatial distance of the observation units (counties) from each other will be taken into account. Spatial statistical models (see below) may then reflect the fact that outcomes in one area are affected by outcomes in neighbouring regions (spatial spillover effects) and/or a spatial autocorrelation of the residuals. Common to all spatial models is the spread of the virus.

The individual independent variables are grouped in the left column of Table 2. The estimated values with the corresponding standard errors in brackets are shown in the following columns for the respective models. Dummies for the 16 federal states were included in the model (estimates not shown) to check for the potential influence of country-specific lockdown measures and their different time frames.²

The estimated coefficients in Table 2 show a rather uniform picture across the three spatial models with regard to their significance and sign. In fact, there are only two variables, women and childcare, for which there are differences in significance (at least at the 10% level) between the three models: Childcare is only (negatively) significant in the SAR model, while women is only (positively) significant in the SEM and SAC models. In detail, it can be seen that, as expected, the early case numbers turn out positively significant (1% level). With regard to the economic variables, in contrast to what is expected (according to the recent media discussion), no significant negative influence of the income variable and no significant positive influence of the unemployment rate can be found. Here, it is also important to point out once again that the results of an ecological study do not necessarily have to correspond with the process of infection at the individual level. However, similar results were reported in Refs. [23,35], for example, and (in contrast to the prevalence of long-term widespread diseases) were attributed to the fact that the spread of the virus is favoured by high economic activity.

Interesting with regard to our second research question (cf. Section 1) is especially the positive influence of employees in the nursing professions across all three models (5% level). Apparently, even after controlling for the number of people in need of care (see further down in the table, not significant), infection numbers seem to be influenced by the number of people employed in care, which would confirm the recent media discussion empirically consistent. On the other hand, the tourist bed sector cannot be significantly associated with infections in our models, although numerous channels of action are conceivable even after the lockdown measures have come into effect. It is possible, however, that these have already manifested themselves in the early case numbers and are therefore largely covered by this variable.

With regard to the employment structure, it is striking that, in contrast to the industry and service share, only the share of academics has a significant (1% level) positive association with infections (across all three models). This may indicate higher economic activity in the respective counties (although the income variable itself remains insignificant) or also increased social contacts favoring the spread of the virus, see also [38]. The result is in line with [35], who reports medium evidence for social connectedness and economic development as determinants of COVID-19 infections at the country level.

The demographic variables reflect the fact that a rising average age has a significantly positive (at least 10% level) influence on the number of cases, whereas the proportion of persons over 75 years seems to have a significantly negative (5% level) influence. This seems to contradict the media presentation that especially elderly people are affected by COVID-19 infections (which seems to apply even to the death figures with regard to Table 3, see below). However, this result can be empirically confirmed for example by Ref. [23] for Catalonia. As a possible explanation, it can again be cited that a high proportion of older persons tends to indicate a regionally lower level of economic and social activity, thus limiting the spread of the virus.

The area of health indicators it is noticeable that the prevalence of

² Called up on 11.06.2020 at https://public.opendatasoft.com/explore/?sort=modified.

³ See e.g. https://www.bundesregierung.de/breg-de/themen/coronavirus/corona-bundeslaender-1745198.
physician density seems to have a significantly reducing effect on the COVID-19 with COPD at individual level. However, a high regional significant positive significant association of a severe course of which means empirical confirmation of common epidemiological density appears to have a significant (1% level) impact on infections, in individual cases is only repeated here, cf [42]. for first results of a models of virus spread and also corresponds to public perception. Note beds and pharmacies.

The significance level symbols are £ mean age 0.57 (0.47) 0.42 (0.47) 0.47 (0.47)

Car density 0.42 (0.61) −0.35 (0.60) −0.37 (0.60)
Commuter balance 0.52 (1.69) 0.37 (1.70) 0.30 (1.71)
Share of foreigners −0.57 (10.88) −5.75 (10.85) −2.85 (11.01)
Immigr. human. reasons 8.59 (21.25) 8.64 (20.76) 8.20 (20.68)
Multi-fam. houses −2.98 (3.68) −1.38 (3.72) −1.64 (3.72)
Regions urban. appr. −13.50 (63.12) −49.40 (66.35) −50.08 (66.31)
Rural regions 28.28 (78.19) −4.35 (81.83) −8.421 (81.93)
Pupils −36.05 (19.50) −39.19* (18.67) −35.43† (18.78)
Childcare −9.04† (4.84) −6.99 (5.03) −7.65 (5.10)

Interactions (centered)
Childcare × mean age 3.35** (1.30) 2.97* (1.30) 3.03* (1.30)
Pupils × mean age 19.04* (8.93) 18.57* (8.53) 18.15* (8.50)
Nursing × mean age 0.57 (0.47) 0.42 (0.47) 0.47 (0.47)
Constant −16728.64** (4347.27) −15734.84** (4307.13) −16324.19** (4323.41)
lambda −1.04** (0.33) −1.04** (0.33) −0.69† (0.49)
rho 1.03** (0.03) 1.06** (0.06)

sigma2 121389.73** (8594.28) 119734.46** (8466.83) 118921.29** (8417.15)
Log likelihood −2917.81 −2917.28 −2916.17
LR ch2 (OLS) 9.51** 10.56** 12.78**
LR ch2 (SAC) 3.27 2.23

The significance level symbols are † for 10%, * for 5%, and ** for 1%.
above the Germany-wide average age, the marginal effect of childcare increases significantly by 3.35 in the SAR model, for example (and by a similar magnitude for the other models). An analogous (significant) interaction effect emerges for pupils. Of course, this means that the negative marginal effect of child care and schoolchildren may even be reversed for regions with a high average age. Thus, childcare and pupils can have a different influence on the incidence of infection depending on a region’s age. This could, for example, be due to the increased probability of infection of population groups above the average age, but cannot be conclusively answered based on region-specific data alone. Nevertheless, this key finding complements and qualifies previous consideration of death numbers as outcome variables is nevertheless justified, since mortality (especially at the beginning of an epidemic) is no means a time-constant variable and therefore the structural similarity of the socio-economic influencing variables compared to the case numbers is not known a priori.

It is particularly interesting that the interaction effects are all insignificant, unlike in Table 2. This means that the (significant) negative marginal effect of childcare and pupils on the number of deaths does not change as a function of the average age of the region. A possible explanation (and an interesting avenue for future research) could be that an infection event in kindergartens and schools does not spill over to populations with increased COVID-19-related mortality (e.g., aged over

### Table 3

| Variable                  | SAR Coef. | (Std. Err.) | SEM Coef. | (Std. Err.) | SAC Coef. | (Std. Err.) |
|---------------------------|-----------|-------------|-----------|-------------|-----------|-------------|
| Early cases               | 0.29**    | (0.07)      | 0.27**    | (0.07)      | 0.27**    | (0.07)      |
| Economy                   |           |             |           |             |           |             |
| HH income                 | −0.00     | (0.01)      | −0.00     | (0.01)      | 0.00      | (0.01)      |
| Unempl. rate              | −0.28     | (1.39)      | −0.57     | (1.38)      | −0.51     | (1.37)      |
| Pers. services            | −0.31     | (0.48)      | −0.51     | (0.48)      | −0.41     | (0.47)      |
| Pers. nursing             | 0.28**    | (0.09)      | 0.30**    | (0.09)      | 0.30**    | (0.09)      |
| Academics                 | 1.13*     | (0.53)      | 1.14*     | (0.55)      | 1.07f     | (0.55)      |
| Industry share            | 0.00      | (0.24)      | −0.01     | (0.23)      | −0.01     | (0.23)      |
| Service share             | 0.07      | (0.25)      | 0.04      | (0.25)      | −0.00     | (0.24)      |
| Tourist beds              | −0.03     | (0.03)      | −0.03     | (0.03)      | −0.03     | (0.03)      |
| Old age pov.              | 0.32      | (0.23)      | 0.35      | (0.23)      | 0.35      | (0.23)      |
| Demography                |           |             |           |             |           |             |
| Mean age                  | 5.70t     | (3.33)      | 5.44†     | (3.26)      | 6.16†     | (3.23)      |
| Over 75                   | −6.71*    | (3.21)      | −6.64*    | (3.18)      | −6.94*    | (3.17)      |
| Women                     | 4.10      | (2.77)      | 4.62†     | (2.74)      | 4.91†     | (2.72)      |
| Health                    |           |             |           |             |           |             |
| Heart failure             | 0.31      | (1.50)      | −0.05     | (1.50)      | −0.52     | (1.52)      |
| COPD                      | −0.26     | (1.27)      | 0.04      | (1.31)      | −0.05     | (1.33)      |
| Physicians                | −1.65†    | (0.78)      | −2.02**   | (0.78)      | −2.06**   | (0.78)      |
| Hospital beds             | −0.72     | (0.57)      | −0.40     | (0.56)      | −0.43     | (0.54)      |
| Pharmacies                | −0.08     | (0.38)      | 0.00      | (0.39)      | −0.17     | (0.39)      |
| Infant mortality          | 0.53      | (0.67)      | 0.52      | (0.66)      | 0.50      | (0.64)      |
| Life expectancy           | 7.11**    | (2.47)      | 6.07†     | (2.47)      | 6.79**    | (2.46)      |
| Need of care              | −0.00     | (0.03)      | −0.00     | (0.03)      | 0.00      | (0.03)      |
| Region                    |           |             |           |             |           |             |
| Pop. density              | 0.01      | (0.00)      | 0.01†     | (0.00)      | 0.01†     | (0.00)      |
| Car density               | 0.02      | (0.04)      | 0.02      | (0.04)      | 0.02      | (0.04)      |
| Commuter balance          | 0.08      | (0.10)      | 0.05      | (0.10)      | 0.08      | (0.10)      |
| Share of foreigners       | −0.14     | (0.66)      | −0.24     | (0.65)      | −0.05     | (0.66)      |
| Immigr. human. reasons    | −0.44     | (1.29)      | −0.40     | (1.26)      | −0.42     | (1.23)      |
| Multi fam. houses         | 0.19      | (0.22)      | 0.25      | (0.22)      | 0.26      | (0.23)      |
| Regions urban. appr.      | 1.62      | (3.82)      | 0.24      | (4.00)      | 0.56      | (4.10)      |
| Rural regions             | 3.20      | (4.72)      | 0.82      | (4.94)      | 1.53      | (5.02)      |
| Pupils                    | −2.13†    | (1.18)      | −2.30*    | (1.13)      | −2.02†    | (1.11)      |
| Childcare                 | −0.51†    | (0.29)      | −0.44     | (0.30)      | −0.54†    | (0.31)      |
| Interactions (centered)   |           |             |           |             |           |             |
| Childcare × mean age      | 0.03      | (0.08)      | 0.02      | (0.08)      | 0.02      | (0.08)      |
| Pupils × mean age         | 0.07      | (0.54)      | 0.08      | (0.52)      | 0.08      | (0.50)      |
| Nursing × mean age        | −0.01     | (0.03)      | −0.02     | (0.03)      | −0.02     | (0.03)      |
| Constant                  | −910.67** | (263.65)    | −840.43** | (260.34)    | −931.62** | (258.98)    |
| lambda                    | −0.66†    | (0.39)      | 0.25      | (0.22)      | 0.26      | (0.23)      |
| rho                       | 0.96**    | (0.04)      | 0.72*     | (0.03)      | 0.72*     | (0.03)      |
| sigma2                    | 446.41**  | (31.57)     | 437.17**  | (30.93)     | 429.97**  | (30.71)     |
| Log likelihood            | −1792.95  | (31.57)     | −1791.47  | (30.93)     | −1789.73  | (30.71)     |
| LR chi2 (OLS)             | 2.84†     | (0.59)      | 5.79      | (2.84)      | 9.27**    | (3.41)      |
| LR chi2 (SAC)             | 6.44†     | (0.59)      | 3.48†     | (0.59)      | 9.27**    | (3.41)      |

3.2. **Death count**

Results for the death counts in relation to COVID-19 are summarized in Table 3. In comparison with the results for the case numbers in Table 2, it is noticeable that the signs and significances for the estimated coefficients are virtually identical. To explain this, it should be taken into account that the death numbers usually represent a percentage (mortality) of the case numbers with a certain time lag. For Germany, this mortality is approx. 4.7% (as of June 15, 2020). However, a separate consideration of death numbers as outcome variables is nevertheless justified, since mortality (especially at the beginning of an epidemic) is a time-constant variable and therefore the structural similarity of the socio-economic influencing variables compared to the case numbers is not known a priori.

Finally, we also included interaction effects for nursing to check whether the positive influence of nursing varies with the average age of the region. It could be that particularly old regions are more sensitive to more nursing than younger regions because infections behave differently due to the high average age. This cannot be confirmed, however, as interactions are insignificant.
3.3. Spillover effects

Regarding our question No. 3 (cf. Section 1) the LR tests implemented in Section 3.1 already support the thesis of a spatial dependency in the data. However, the question of actual regional spillover effects remains unanswered so far. In Ref. [9] it is proposed to analyze these spatial spillover effects by calculating the so-called (average) indirect effects (where the coefficients reported in Tables 2 and 3 correspond to the so-called direct effects). The indirect effects reflect how a change in the \( k \)-th independent variable of region \( j \) affects cases (or deaths) in region \( i \), as the result of an infinite sequence of spatial feedback effects. Since these effects naturally vary by region, summary measures have been proposed as quasi-average spillover effects and are reported in what follows. For technical details see e.g. Ref. [19].

To keep the presentation clear, we restrict ourselves in Table 4 to the significant indirect effects (where we also report the corresponding total effects reflecting the sum of the direct an indirect effects). Note that the SEM model has no spillover effects and is therefore omitted in Table 4.

In terms of interpretation, it should be noted that the significant negative spillover effects of early cases may indicate that early lockdown measures in affected regions and increased awareness and thus caution about COVID-19 were successful in preventing the spread of cases to neighboring regions. However, some of the results in Table 4 should be interpreted with caution and in a more hypothesis-generating manner at the current state of (ecological) research. Given the significant negative spillover effects of mean age (meaning, in other words, that areas with a higher mean age have a protective effect on surrounding areas with respect to COVID-19 infections), it could be argued that age-related reduced travel to neighboring regions leads to a containment effect on the number of cases there. In contrast, the significant positive spillover effects related to over 75 could indicate that economic activity in the corresponding region is low due to age (hence the negative direct effect), but mobility of dependents (visitors) across county borders is rather high (hence the positive spillover effects). Further, the significant negative spillover effects of the nursing variable could be due to the fact that a concentration of nursing homes (other than a mere high percentage of the population over 75 as above) has a protective effect on surrounding counties, as nursing homes in Germany were closed off at an early stage of the pandemic by strict lockdown measures.

On the other hand, the density of doctors seems to lead to significant positive spillover effects, since here, in contrast to the nursing homes, increased patient traffic across regional borders is to be expected. The same argument (i.e., exporting infections to surrounding regions) seems plausible as an explanation for the significant positive spillover effects of pupils, since the location of schools often differs from their place of residence. Finally, it is interesting to note that the number of beds in tourist establishments does not seem to lead to significant spillover effects in neighbouring regions (not significant, not included in the table). Here, for example, the early restrictions on tourist travel in the context of the imposed contact restrictions could play a role.

Regarding the results for death count (not shown), only the variables nursing (negative), physicians (positive), and life expectancy (negative) show significant spillover effects. Since the signs correspond to those of the spillover effects for the case numbers, arguments similar to those above can be referred to for explanation.

4. Discussion

This ecological study addresses the association of socio-economic variables with COVID-19 infections and deaths. Data at the district level and spatial econometric models are applied to capture indirect spillover effects between the individual districts. In particular, we asked three research questions about the role of schools and child care, the role of nursing homes, and spatial spillover effects on infections and deaths.

To highlight a key result, we have found that the density of pupils and the care rate of small children (kindergartens) seems to have a rather dampening (i.e. negative) effect on infections. However, the average age at the district level turned out to be a moderator effect, i.e. for regions with older population, this negative effect is mitigated (and can even be turned into positive). This result underlines that a general statement on the effect of kindergartens and schools on infection is not possible, but is at least qualified by an age variable. The task of future research can be to confirm these effects (possibly also on the basis of individual data) and possibly to uncover further significant moderator variables not discussed in this study.\(^4\)

A possible limitation to this conclusion regarding schools and daycare centers can be discussed in view of the testing strategy followed in Germany, which does not guarantee that children are tested as regularly as adults. Thus, it could be argued that schools and day care centers stand as a mere indicator for a high number of undetected cases. As background information, it should be mentioned that, according to the national testing strategy, testing only follows the appearance of typical COVID-19 symptoms, whereas children are known to have a rather asymptomatic course. Unfortunately, no systematically collected data of the performed tests by age group and region are available for the period of the study. However, a (not regionally disaggregated) sample of voluntarily participating laboratories (about 30% of all testing laboratories), which continuously report their test results to the RKI, can be used as a first indication [33]. The results show that the proportion of tests performed among 0–4 year olds (at about 0.9% of the population) is indeed lower than for the overall average (about 1.8% of the population). However, the positive rate for 0–4 year olds (1.8%) is also more than half lower than the overall positive rate (about 4.4%) for all tests conducted by mid-June 2020. This consideration can at least partially consolidate our conclusion on kindergartens and schools (even if it cannot rigorously prove it): After all, equalizing the testing rate for children based on the above figures would tend to reduce the overall

\(^4\) Note that a single study should not include an arbitrary number of model variations in order to still ensure (against the background of a multiple comparisons problem) a statistically meaningful interpretation of the significance levels.
positive rate in the population. However, even if the empirical arguments just mentioned (due to lack of data and regional context) should not be considered rigorous and conclusive, there is also a similar tendency in the current body of research to suggest that schools and daycare centers are not seen as drivers of COVID-19 caseloads, which also supports our conclusion, see Refs. [6,26,37] for Germany and [7,16,18,31] for an international perspective. These studies also provide some plausible (albeit yet to be further explored) mechanisms of action that could help explain our ecological conclusion regarding schools. These include, for example, the organized and more aumenable to public hygiene measures environment in daycare centers and schools versus the largely uncontrollable situation in children’s homes. In addition, the presence in daycare centers and schools provides reliable daily access to up-to-date information on COVID-19 for children and parents. Added to this is the role of daycare centers and schools as learning sites for COVID-19-compliant behavior and active practice of hygiene concepts. However, positive spillover effects of pupil density to neighbouring regions could be observed, so this cross-regional export or import of infections due to schools and childcare should be carefully analysed also in future individual-level studies.

Turning to our second question, namely the role of care for the elderly and the employees in this area, first significant indications could be found. The results show that the sole quota of persons in need of care has no influence on infections and deaths, whereas the influence of the employment density in this sector on both outcomes turns out to be significantly positive. These results are all the more interesting because they also support the anecdotal ongoing evidence from the media about nursing homes as hotspots of COVID-19 dissemination and even differentiate between the different outcomes for residents and employees. However, it must be mentioned as a limitation that our data do not distinguish between day care at home and nursing homes.

We were also able to find clear evidence regarding our third question of spillover effects between neighbouring districts, which, to our knowledge, has not been investigated empirically for COVID-19 in Germany before. On the one hand, the suitability of spatial models compared to simple OLS approaches is statistically supported. On the other hand, indications of negative effects (i.e. a containment effect on neighbouring regions) could be found especially for the number of early cases of infection or the average age, whereas spillover effects for doctor and pupil density turn out to be positive. Since this means an export of infections across regional borders, these questions should be analysed in future studies in greater detail and, if possible, on an even smaller regional scale, in order to expand the knowledge about the ecological pathways of COVID-19 transmission.

The practical relevance of the results lies, among other things, in the derivation of new or adaptation of existing political measures for the containment of COVID-19, which by their very nature also do not function at the individual level, but at the population level. When interpreting these ecological results, different mechanisms of action, namely the numerous interdependent infection channels at population level, than in clinical or biological studies at individual level must be taken into account. To give one example: Certainly, a high social status, which can be sufficiently measured e.g. by income, at least statistically protects against infection or even death from COVID-19 at the individual level. Well-known mechanisms of action from the literature can include

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At least under the weak assumption that the unobserved positive rate among children who have not been tested so far because they are asymptomatic does not exceed that of those who have been tested, which can be considered plausible.

physical networking), travel and social contacts such as working with colleagues in teams or open-plan offices. In other words, both results can be empirically substantiated and are therefore not contradictory.

Our results have proven to be stable in numerous robustness checks: First, the three model types applied (SAR, SEM, SAC) show very comparable results with respect to our core results. In addition, the calculation of the weighting matrix was varied (using the normalize option in Stata) and the robustness of the age (±5 years) and date (±2 weeks) cutoffs was checked. Also, the possible influence of other health variables, such as specialist density or development of hospital care over the last 5 years, had practically no impact on our results. From a statistical perspective, there are further avenues for future studies, e.g., in the area of modeling the temporal dynamics of case numbers, which were explicitly not the subject of this analysis, cf. the generalized additive mixed model approach in Ref. [22] or the dynamic spatial Durbin panel models discussed in Ref. [10]. Finally, there is also the question of comparing the results with corresponding regional analyses for other countries.

Declaration of competing interest

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A computer movie simulating urban growth in the detroit region. Econ Geogr 1970;46:234–40.

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