Wave after wave – Determining the temporal lag in Covid-19 infections and deaths using spatial panel data from Germany

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Research Article

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Posted Date: July 12th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-447920/v1

Wave after wave – Determining the temporal lag in Covid-19 infections and deaths using spatial panel data from Germany

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JEL Codes: C21, C23, I10, I18

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declarations of interest: none

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Abstract – The Covid-19 pandemic requires a continuous evaluation of whether current policies and measures taken are sufficient to protect vulnerable populations. One quantitative indicator of policy effectiveness and pandemic severity is the case fatality ratio, which relies on the lagged number of infections relative to current deaths. The appropriate length of the time lag to be used, however, is heavily debated. In this article, I contribute to this debate by determining the temporal lag between the number of infections and deaths using daily panel data from Germany's 16 federal states. To account for the dynamic spatial spread of the virus, I rely on different spatial econometric models that allow not only to consider the infections in a given state but also spillover effects through infections in neighboring federal states. My results suggest that a wave of infections within a given state is followed by increasing death rates 12 days later. Yet, if the number of infections in other states rises, the number of death cases within that given state subsequently decreases. The results of this article contribute to the better understanding of the dynamic spatio-temporal spread of the virus in Germany, which is indispensable for the design of effective policy responses.

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1. Introduction

By the end of 2019, a novel coronavirus, the severe acute respiratory syndrome coronavirus 2, in short Covid-19, was detected in the city of Wuhan in China (Guan et al., 2020; Zhang et al., 2020). What seemed first to cause only a country wide epidemic has fast developed into a worldwide pandemic, which is by now judged as the greatest human challenge since the Second World War. By the time of April 2021, the pandemic has caused almost 130 million infections and more than 2.8 million deaths worldwide.

As a policy response, several countries implemented severe lockdowns, including school and store closings, curfews and travel bans to reduce human interaction and thereby the spread of the virus. While aiming to save human life, such restrictions also limit human freedoms. Hence, they require a continuous evaluation of whether they are sufficient to protect vulnerable populations and whether more or less strict measures can and should be considered. One quantitative indicator of policy effectiveness and pandemic severity is the case fatality ratio (WHO, 2020; Ioannidis, 2021), which is based on the lagged number of infections relative to current deaths. The appropriate length of the time lag to be used, however, is heavily debated (Baud et al., 2020; Kim and Goel, 2020). An accurate measure is essential as both, over and underestimation can have severe consequences, such as not taking the pandemic seriously or causing redundant panic (Kim and Goel, 2020).

The literature reflects the uncertainty about the appropriate length. Chrusciel and Szybka (2021), for example, investigate the time lag in several European countries and find that the lag between reported cases and deaths averages around seven days. Vanella et al. (2020) also investigate the appropriate time lag for European countries to calculate an unbiased case fatality ratio and conclude that a lag between five and ten days should be used. Testa et al. (2020) determine the lag for US counties and find a substantially longer lag. They conclude that deaths often occur two to eight weeks after the onset of the first symptoms. Wilson et al. (2020) determine the case fatality ratio for China and find that a 13-day lag best describes the pattern of the data.

To add to this debate, I provide rigorous evidence for the length of the time lag between a rise in infections and a subsequent rise in death cases using daily panel data for Germany's 16 federal states

from May 2020 to December 2020. In comparison to the studies outlined above, however, I rely on a spatial econometric approach to consider the dynamic spatial spread of the virus. I thereby also add to the literature that analyses the dynamics of Covid-19 and quantifies the spatio-temporal interactions and spillovers of the virus (e.g., Ehlert, 2020; Guliyev, 2020; Krisztin et al., 2020). Specifically, I estimate different spatial econometric models that allow not only to consider the infections in a given state but also those in neighboring states, so-called spatial lags. Spatial econometric models are useful to model interaction effects between geographical units (Elhorst, 2021) and are hence especially useful to model the global-spreading and infectious nature of the coronavirus.

I determine the lag between the wave of infections and the wave of Covid-19 casualties in Germany's federal states and their geographical spread with four spatial models: I use (1) a model with spatial lags in the independent variables (SLX model), (2) a non-dynamic and (3) a dynamic model that include spatial lags in both, the dependent and independent variable, together with space and time fixed-effects (Spatial Durbin Models with fixed-effects), and (4) a dynamic Spatial Durbin Model with common factors (i.e., cross-sectional averages instead of time fixed-effects). These models allow to derive the direct (same-state) and indirect (other states) effects of infections on death cases.

The remainder of this article proceeds as follows. In Section 2, I present the data used for the analysis. In Section 3, I outline the empirical strategy and briefly discuss the differences in the spatial econometric models. I present the results in Section 4 and conclude in Section 5.

2. Data

Daily infections and daily death cases

The main variables used in this article are the number of daily infections and the number of daily reported death cases due to Covid-19 in Germany at the federal state level. There are in total 16 federal states and the German *Robert Koch Institut* (RKI) provides and updates the respective numbers on a daily basis since the very beginning of the pandemic.[2] Yet, as the number of cases in the first and second wave are not directly comparable (due to different testing strategies and measures taken), I make use of

[2] https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Fallzahlen.html.

the data from the period between May 1, 2020 to December 31, 2020, hence dropping observations from the first wave's peak as well as those that were recorded after the vaccination campaign started. The latter is done to get an estimate of the time lag between infections and deaths without the vaccine being available, hence, an unbiased measure of when the rise of deaths should be expected after a rise of infections.

Population and geospatial data

To make the numbers of infections and deaths comparable across the different states, I calculate them per 100,000 inhabitants in the respective state. The corresponding population numbers are derived from the *Bundesamt für Kartographie und Geodäsie*[3] which provides geospatial shape files for Germany, including population numbers for each state. The same source is used to derive the geographical coordinates for each state, which are essential to construct the spatial weight matrix used in spatial models (see Section 3).

Intensive care cases

To be able to derive an unbiased estimate of the time lag between infections and death cases, I control for the number of intensive care (IC) cases per federal state, i.e., the number of patients that have contracted the corona disease and are under intensive care. This number might be positively related to both variables of interest, the number of infections and deaths. Hence, including the variable in the regression avoids an upward omitted variable bias. Information on the number of patients in IC is provided by the RKI and the German Interdisciplinary Group for Intensive and Emergency Care (DIVI).[4] The data are available on a daily level and per federal state.

Temperature data

The medical literature reports that respiratory diseases and infections follow seasonal cycles and are susceptible to temperature (e.g., Shaman et al., 2010; Martinez, 2018). Similar patterns have recently been confirmed for the coronavirus. Ma et al. (2020), in their analysis on temperature and humidity

[3] See http://sg.geodatenzentrum.de/web_download/vg/vg250_0101/vg250_0101.pdf for a description of the data set.
[4] https://www.intensivregister.de/#/index.

effects on Covid-19 deaths in China, find that higher temperatures lead to increases in death cases. Wu et al. (2020) contrarily identify a negative relationship between temperature and new cases and deaths in a study on 166 countries. To control for the potential confounding factor of temperature, I include the daily mean temperature on the state level in my analysis. Data on daily meteorological conditions is received from the German Weather Service (DWD). The DWD provides daily time series data for 538 weather stations across Germany, including the coordinates of each station. I merge each station to the corresponding federal state, using their coordinates, and average the mean temperature across all stations.

Figure 1 shows the spatial distribution of the number of infections per 100,000 inhabitants per state cumulated over the observation window from May 1, 2020 to December 31, 2020. The figure shows a clear variation in the number of cumulative Covid-19 cases across all federal states. From a first glimpse, cross-sectional dependence seems to be present as there is some clustering of states with similar infection rates.

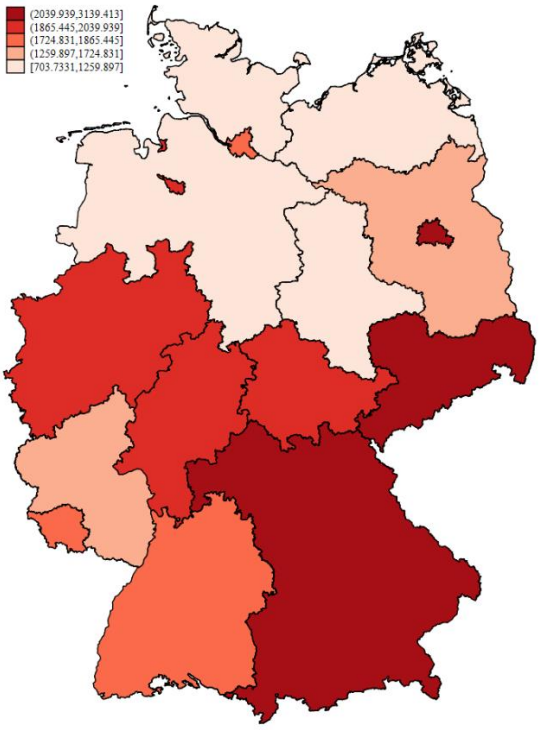

Figure 1: Cumulative Covid-19 infections in Germany. *Notes:* The map shows the cumulative number of Covid-19 infections per 100,000 inhabitants between May 1, 2020 and December 31, 2020 for the 16 federal states in Germany.

To confirm the presence of cross-sectional dependence statistically, I use Pesarans's CD-test for panel data (Pesaran, 2004, 2015), which is based on the pairwise correlation coefficients of the different geographical units. I also estimate the cross-sectional exponent α (Bailey et al., 2016) to determine the degree of cross-sectional dependence. The results are shown in Table 1 and confirm the cross-sectional dependence for the number of infections. Cross-sectional dependence is also confirmed for deaths, the number of IC patients and temperature. The correlation is in each case significant at the 1% level and very strong as the exponent α indicates. This suggest that a model with cross-sectional averages ('common factors') instead of time fixed-effects might be better suited to capture the cross-sectional dependence (Elhorst et al., 2021).

Table 1: Pesarans' CD test for cross-sectional dependence and cross-sectional exponent α

Variable	**CD-test**	**p-value**	**Corr.**	α
Deaths	135.74	0.000	0.744	1.00
Infections	152.62	0.000	0.847	1.00
Intensive care patients	164.70	0.000	0.945	1.00
Mean temperature	170.05	0.000	0.963	1.00

Notes: The null-hypothesis is weak cross-sectional dependence.

3. Empirical Strategy

To identify the time lag between the number of cases and the number of deaths, I rely on a spatial econometric approach, which allows me to model direct effects within the geographical unit of interest, while accounting for possible interaction effects with neighboring spatial units. Elhorst (2021) differentiates between three types of interactions: (1) exogenous interactions effects (i.e., the independent variable in one spatial unit can affect the dependent variable in other spatial units), (2) endogenous interaction effects (i.e., the dependent variable in one spatial unit can affect the dependent variable in other spatial units), and (3) interaction effects among the error terms (i.e., the error term in one unit can affect the error term in other units). In the modeling approach outlined below, I consider endogenous and exogenous interaction effects.

I use the number of daily deaths per 100,000 inhabitants within each state as dependent variable and regress it on the same-day number of new infections per 100,000 inhabitants in the same state as well

as on the number of new infections per 100,000 inhabitants up to 14 days lagged in time in the same state. As explained above, I do control for the number of patients being treated in IC as well as for mean temperature. Both variables also enter the regression with in total 14 time lags. Moreover, I include state fixed-effects to control for all non-time-varying effects that are specific to each state (such as being located at the sea or at the border to a different country) and which might impact the number of daily death cases and infections. Also, day fixed-effects are included to control for time effects affecting all states similarly. This will, for example, control for the effect of the whole country being in lockdown as well as for week-day specific patterns, such as fewer tests during the weekend.

So far, this model corresponds to a 'standard' distributed lag model with fixed-effects. To account for the spatial dependence, I further add the spatial components to the model. The full model reads

$$\begin{aligned} Deaths_{it} = \tau Deaths_{it-1} + \rho \sum_{j=1}^{N} w_{ij} Deaths_{jt} + \eta \sum_{j=1}^{N} w_{ij} Deaths_{jt-1} + \\ \sum_{k=0}^{14} \beta_k Infections_{it-k} + \sum_{k=0}^{14} \theta_{1k} \sum_{j=1}^{N} w_{ij} Infections_{jt-k} + \sum_{k=0}^{14} \delta_k Temperature_{it-k} + \\ \sum_{k=0}^{14} \theta_{2k} \sum_{j=1}^{N} w_{ij} Temperature_{jt-k} + \sum_{k=0}^{14} \gamma_k Intensive_{it-k} + \\ \sum_{k=0}^{14} \theta_{3k} \sum_{j=1}^{N} w_{ij} Intensive_{jt-k} + \alpha_i + \sigma_t + u_{it}, \end{aligned} \quad (1)$$

where w_{ij} are the elements of the matrix $\boldsymbol{W}$, which is a 16 × 16 row-normalized binary contiguity matrix, with its elements being equal to one when state *i* and state *j* are neighboring states and zero otherwise, and all diagonal elements w_{ij} with $i = j$ equal to zero.[5] α_i and σ_t are the federal state and time fixed-effects, respectively. $Deaths_{it}$, $Infections_{it}$ and $Intensive_{it}$ are the respective numbers of death cases, infections and intensive care patients per 100,000 inhabitants at day *t* in state *i*. $Temperature_{it}$ is the mean temperature at day *t* in state *i*. The subscript *j* always denotes all states excluding state *i*. u_{it} is the error term. k is an index running from 0 to 14 and indicates the respective time lag. The parameters $\eta, \rho, \theta_{1k}, \theta_{2k}$ and θ_{3k} jointly determine the spatial interaction effects. The main parameters of interest to determine the time lag are the parameters β_k and θ_{1k}. However, the point estimates cannot directly be interpreted as the direct effects and the spillover effects (except in the SLX model), but have to be

[5] $\boldsymbol{W}$ can also be defined as inverse distance matrix, where the elements w_{ij} are the inverse of the distance between state *i* and state *j*. I also estimated all models using an inverse distance matrix, but this specification performed statistically worse in every model.

calculated separately. Specifically, as soon as endogenous interaction effects enter the regression, the direct effect is calculated as the average diagonal element of the models' reduced form matrices (in matrix notation) $(\mathbf{I}-\rho\mathbf{W})^{-1}[\beta_k+\mathbf{W}\theta_k]$, where **I** is the identity matrix. The indirect effect is the average row sum of the off-diagonal elements of the same reduced form matrices (LeSage and Pace, 2009; Elhorst, 2021).

I estimate five different specifications of the outlined model by constraining several of the parameters. In Model (1), I set $\tau = \eta = \rho = \theta_1 = \theta_2 = \theta_3 = 0$, resulting in the standard distributed lag model with fixed-effects. With these restrictions, no spillover effects can occur.

In Model (2), I set $\tau = \eta = \rho = 0$, such that the model is the SLX model (spatial lag in independent variables). This model allows only to derive long-run and only local spillover effects, i.e., only neighboring states can affect each other.

In Model (3), I allow ρ to be different from 0 and only set $\tau = \eta = 0$, leading to a non-dynamic Spatial Durbin Model with fixed-effects. Finding the parameter ρ to be significantly different from zero implies global spillover effects, since also non-neighboring states can (through other states) affect each other. The non-dynamic model, however, does not allow to differentiate between short-term and long-term effects.

Allowing all parameters to differ from zero results in Model (4), the dynamic Spatial Durbin Model with fixed effects. Adding the dynamic element allows also to differentiate between short-term and long-term effects. In Model (5), I drop the time fixed-effects and instead include three common factors, i.e., the cross-sectional averages for $Deaths_{it}, Deaths_{it-1}$ and $Infections_{it}$, to take into account that the cross-sectional exponent α is equal to one for all variables. All four spatial econometric models have the advantage that the spillover effects are fully flexible, i.e., they can take any value, which makes them more suitable for economic research focusing on spillover effects in comparison to a Spatial Autoregressive Model (SAR) or Spatial Autoregressive Combined Model (SAC) (Elhorst, 2021).

4. Results

Table 2 presents the regression coefficients for each of the models outlined above. Table 3 presents in addition the direct effects and spillover effects. Column (1) in Table 2 displays the results for the standard linear distributed lag model with fixed-effects, where the point estimates of the parameters can be interpreted directly. It shows, as expected, that the number of daily infections is a strong determinant of the number of deaths cases. An interesting pattern can be observed: the number of the same day infections positively relates to the same day number of deaths cases, while the first lag is negative. This suggests that some form of mortality displacement is present, i.e., a temporary increase in death cases is followed by days with decreased death cases. While this phenomenon has especially been observed during heat waves (see for example Deschênes and Moretti, 2009; Karlsson and Ziehbart, 2018), studies also investigate this phenomenon in the context of Covid-19 (Michelozzi et al., 2020; Cerqua et al., 2021). The number of infections four and five days lagged also positively and significantly relates to the death cases, followed once again by negative effects at nine and ten days lagged, and then turning once again positive and significant at lag 12 to 14. Hence, this first basic model suggests that the number of Covid-19 death cases rises in two waves after an increase in the number of infections. Once after four to five days and again after 12 days. The 15 coefficients for the daily mean temperature are insignificant, while four out of the 15 coefficients for the intensive care variable are significant, yet without a clear pattern (coefficients for *temperature* and *intensive care cases* are not shown in the Table). This model, however, does not yet account for spatial interdependence. Also, the residual CD-test reveals that the test statistic does not lie within the interval [-1.96; 1.96], which is needed to conclude that there is no further cross-sectional dependence in the residuals.

Moving to the SLX model in Column (2) allows to make a first statement about local spillovers. They show that the number of infections in neighboring states *j* also significantly relates to the death cases in state *i.* The spillover effects are quite similar in size to the direct effect and suggest that an increase in infections in neighboring states leads first to a decrease in own-state death cases with an eight to ten-day lag and afterwards to an increase in own-state death cases with a 12 to 13-day lag. Specifically, the coefficients suggest that an increase in infections of 100 per 100,000 inhabitants within a given federal state would lead to three to four more deaths after 12 to 13 days, while an increase in infections of 100

per 100,000 inhabitants in neighboring federal states would lead to six more deaths after 12 to 13 days. As before, the direct and indirect effects for temperature are insignificant and those for the intensive care patients inconclusive (shown in Table A1 and A2 in the Appendix). The residual CD-test statistic does again not allow to conclude that this model well captures all cross-sectional dependence.

Column (3) displays the results for the non-dynamic SDM with fixed effects, which includes also an endogenous interaction effect. The coefficient ρ is significantly negative and several of the θ_{1k} coefficients turn negative or insignificant. Calculating the indirect long-run effects (Table 3) shows that they are also insignificant, suggesting that there are no spillover effects. Looking at the test statistics shows that the R-squared value is lower than for the two previous models, and also that the residual CD statistic is still significant, which leads to a rejection of the model.

Introducing the dynamic model in Column (4) shows a somewhat different picture for the ρ coefficient, which now turns significantly positive. The positive significant value of τ suggests serial correlation in the number of deaths. The direct effects are again positive and statistically significant after 12 days, while the indirect effects are zero. R-squared becomes somewhat larger, yet the log-likelihood ratio rejects the model in favor of the non-dynamic model in Column (3). Also, the CD-test statistic lies still outside of the [-1.96; 1.96] interval, leading to a rejection of the dynamic SDM with fixed effects.

Table 2: Estimation results of the lag between Covid-19 infections and deaths using different model specifications

	(1) Fixed Effects	(2) SLX	(3) Non-dynamic SDM with fixed effects	(4) Dynamic SDM with fixed effects	(5) Dynamic SDM with CSA
Deaths t-1 (τ)				0.158***	-0.076***
				(0.016)	(0.016)
WDeaths t (ρ)			-0.189***	0.183***	0.075***
			(0.022)	(0.022)	(0.021)
WDeaths t-1 (η)				-0.007	0.068**
				(0.030)	(0.027)
Infections t	0.017***	0.017***	0.016***	0.016***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Infections t-1	-0.002***	-0.001**	-0.002***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infections t-2	0.000	0.001	0.001	0.001*	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Infections t-3	0.000	0.001	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Infections t-4	0.001*	0.001	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Infections t-5	0.002**	0.002**	0.001**	0.001**	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Infections t-6	0.001	0.000	0.001	0.001	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Infections t-7	0.000	-0.000	0.000	0.000	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infections t-8	0.001	0.000	0.001	0.001	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infections t-9	-0.005***	-0.006***	-0.005***	-0.005***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infections t-10	-0.003***	-0.004***	-0.003***	-0.003***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infections t-11	0.000	0.000	0.000	0.001	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infections t-12	0.004***	0.004***	0.005***	0.005***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infections t-13	0.004***	0.003***	0.003***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Infections t-14	0.004***	0.004***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
WInfections t		0.001	0.001	0.001	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
WInfections t-1		0.003**	0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
WInfections t-2		-0.002	0.003***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
WInfections t-3		-0.001	-0.001	-0.002*	0.001*
		(0.001)	(0.001)	(0.001)	(0.001)
WInfections t-4		-0.001	-0.004***	-0.004***	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
WInfections t-5		0.001	-0.001	-0.001	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
WInfections t-6		0.005***	-0.000	-0.000	0.001**
		(0.001)	(0.001)	(0.001)	(0.001)
WInfections t-7		0.001	-0.001	-0.001	0.001
		(0.002)	(0.001)	(0.001)	(0.001)
WInfections t-8		-0.005***	-0.004***	-0.003***	-0.002***
		(0.002)	(0.001)	(0.001)	(0.001)
WInfections t-9		-0.003**	-0.003***	-0.002**	-0.000
		(0.002)	(0.001)	(0.001)	(0.001)
WInfections t-10		-0.003**	-0.002**	-0.002*	0.000
		(0.002)	(0.001)	(0.001)	(0.001)
WInfections t-11		0.003*	0.001	0.001	0.001*

		(0.002)	(0.001)	(0.001)	(0.001)
WInfections t-12		0.006***	0.001	0.001	-0.000
		(0.002)	(0.001)	(0.001)	(0.001)
WInfections t-13		0.006***	0.001	0.000	-0.001**
		(0.002)	(0.001)	(0.001)	(0.001)
WInfections t-14		-0.000	-0.001	-0.001	-0.001**
		(0.002)	(0.001)	(0.001)	(0.001)
R^2	0.814	0.828	0.716	0.74	0.88
Log Likelihood	[a]	[a]	2564.7862	1084.5405	3255.9895
Residual CD-Test	-9.67	-9.92	62.75	57.44	-0.71
Number of Obs.	3920	3920	3920	3904	3904
Number of Fed. States	16	16	16	16	16

Notes: Standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1. [a] The basic fixed-effects model and the SLX model are estimated with OLS, hence, the Log Likelihood statistic is not available.

The only model that is well suited to fully capture the cross-sectional dependence in the data is the dynamic SDM with cross-sectional averages presented in Column (5), which aligns with the cross-sectional exponent α of one that was estimated for the data. R-squared and the log-likelihood value both take on the largest value in this model and the residual CD-test statistic lies within the [-1.96; 1.96] interval and is, hence, no longer significant. Moreover, the sum of τ, η and ρ is smaller than one, which is essential for the model to be stationary. Interestingly, the model does only account for the full cross-sectional dependence when three cross-sectional averages are included (namely the cross-sectional averages of $Deaths_{it}, Deaths_{it-1}$ and $Infections_{it}$). Including only the cross-sectional averages of $Deaths_{it}$ and $Deaths_{it-1}$ results in a residual CD-test statistic that is still outside the required interval.

Several of the θ_{1k} coefficients as well as the coefficients ρ and η are statistically significant. The significant coefficients jointly indicate that global short-term and long-term spillover effects are present.

The direct effects of increases in the own-state infections are, as expected, positive and significant, which is in line with the hypothesis that increases in infections are followed by increases in deaths. τ is statistically significant and negative, supporting again the hypothesis of mortality displacement, i.e., days with high numbers of death cases are followed by days with low numbers of death cases. The time lag between an increase in infections and a subsequent increase in death cases can be determined at 12 days. Before the 12th lag, the coefficients for both, the direct and the total effect, switch between a negative and positive sign, but become consistently positive afterwards in every model.

In contrast, the estimated indirect effects are significantly negative, indicating that increases in infection rates in other states decrease own-state death cases. This seems counterintuitive at first, but can be an indicator that states choose to implement stricter preventive policy measures in their own state when the infections in other states rise. This is also in line with previous studies. Ehlert (2020), for example, finds that in a given German district the number of deaths and infections shrink with higher numbers in early Covid-19 infections in neighboring districts. Krisztin et al. (2020) also find a temporarily negative degree of global spatial autocorrelation and explain their finding with temporary travel bans to regions with excessive infection rates to prevent transmission to the own country.

Table 3: Direct effects and spillover effects for infections, short-run and long-run

		SR Direct	SR Indirect	SR Total	LR Direct	LR Indirect	LR Total
SLX	Infections t-11				0.000	0.003*	
	Infections t-12				0.004***	0.006***	
	Infections t-13				0.003***	0.006***	
	Infections t-14				0.004***	-0.000	
ND-SDM-FE	Infections t-11				0.000	0.001	0.001
	Infections t-12				0.005***	-0.000	0.005***
	Infections t-13				0.003***	0.000	0.004***
	Infections t-14				0.004***	-0.001	0.003**
D-SDM-FE	Infections t-11	0.001	0.001	0.002*	0.001	0.001	0.002*
	Infections t-12	0.005***	-0.000	0.004***	0.005***	-0.000	0.005***
	Infections t-13	0.003***	-0.000	0.003***	0.003***	-0.000	0.003***
	Infections t-14	0.004***	-0.001	0.003**	0.004***	-0.001	0.003**
D-SDM-CSA	Infections t-11	-0.001*	0.001**	0.000	-0.001*	0.001*	0.000
	Infections t-12	0.002***	-0.000	0.001**	0.002***	-0.000	0.001**
	Infections t-13	0.002***	-0.001**	0.000	0.002***	-0.001**	0.000
	Infections t-14	0.003***	-0.002**	0.002**	0.003***	-0.001**	0.002**

Notes: Table 3 shows the direct and spillover effects, in the short-run and long-run for every spatial model from day t-11 to day t-14. The results for day t to day t-10 are omitted for the sake of space, but are available on request. ***p<0.01, **p<0.05, *p<0.1. SLX: Spatial lag of X model; ND-SDM-FE: non-dynamic Spatial Durbin Model with fixed effects; D-SDM-FE: Dynamic Spatial Durbin Model with fixed effects; D-SDM-CSA: Dynamic Spatial Durbin Model with Cross-Sectional Averages; SR: short-run; LR: long-run.

The coefficients for temperature remain insignificant in every model and both, the short run and long run direct and indirect effects are essentially zero (shown in Table A1 in the Appendix). Hence, in contrast to studies in different settings (Ma et al., 2020; Wu et al., 2020), temperature seems not to affect the number of daily deaths in Germany. Yet, this can at least to some extent be explained by the inclusion of time fixed-effects or common factors, respectively, as they absorb a substantial part of the within-day variation in temperature across states. The number of patients being treated in intensive care seems to

relate to the number of deaths (see table A2 in the Appendix), yet no clear positive or negative pattern emerges.

5. Conclusion

The severe restrictions and policies that are implemented to limit the dynamic spread of Covid-19 require a continuous evaluation to assess their effectiveness. In this regard, the case fatality ratio is one of the most important quantitative measures (WHO, 2020; Ioannidis, 2021). Yet, its calculation requires an exact estimate of the time lag between infections and deaths. In this article, I analyze this lag using daily spatial panel data of the 16 German federal states over the period May 2020 to December 2020. My results suggest that the curve of death cases follows the curve of infections with a lag of approximately 12 days.

Moreover, to account for the spatial spread of the virus, I use spatial econometric models that allow for exogenous and endogenous spillover effects between states. I find that only the dynamic Spatial Durbin Model with state-fixed effects and cross-sectional averages can fully capture the cross-sectional dependence in the data. While the overall effect is positive, the direct and indirect effects differ in sign. The direct effects show that an increase in infections within a given state leads to an increase in the number of reported death cases. Contrarily, the indirect effects (spillovers) are significantly negative, indicating that an increase in infections in neighboring states (and via the global spillovers also in all other states) reduces the number of death cases in that given state. This can be explained by preventive measures taken by the state government as soon as they observe rising infections in other states. While this is well line with the findings of earlier studies (Ehlert, 2020; Krisztin et al., 2020), future studies should investigate the causal underlying reasons in more detail.

References

Bailey, N., Kapetanios, G., Pesaran, M.H. (2016). Exponent of cross-sectional dependence: estimation and inference. *Journal of Applied Econometrics, 31*(6), 929-960.

Baud, D., Qi, X., Nielsen-Saines, K., Musso, D., Pomar, L., Favre, G. (2020). Real estimates of mortality following COVID-19 infection. *The Lancet Infectious Diseases, 20*(7), 773.

Cerqua, A., Di Stefano, R., Letta, M., Miccoli, S. (2021). Was there a COVID-19 harvesting effect in Northern Italy?.[Preprint] arXiv. https://arxiv.org/abs/2103.01812v3.

Chrusciel, P., Szybka, S. (2021). On the lag between deaths and infections in the first phase of the Covid-19 pandemic. [Preprint] medRxiv. https://doi.org/10.1101/2021.01.01.21249115.

Deschênes, O., Moretti, E. (2009). Extreme weather events, mortality, and migration. *The Review of Economics and Statistics*, *91*(4), 659-681.

Ehlert, A. (2020). The socioeconomic determinants of COVID-19: A spatial analysis of German county level data. [Preprint] MedRxiv. https://doi.org/10.1101/2020.06.25.20140459.

Elhorst, J.P. (2021). Spatial Panel Models and Common Factors. In: Fischer, M., Nijkamp, P. (eds). *Handbook of Regional Science*. Berlin, Heidelberg: Springer.

Elhorst, J.P., Gross, M., Tereanu, E. (2021). Cross-sectional dependence and spillovers in space and time: where spatial econometrics and Global VAR models meet. *Journal of Economic Surveys, 35*(1), 192-226.

Guan, W.J., Ni, Z.Y., Hu, Y., Liang, W.H., Ou, C.Q., He, J.X., et al. (2020). Clinical characteristics of coronavirus disease 2019 in China. *New England Journal of Medicine*, *382*(18), 1708-1720.

Guliyev, H. (2020). Determining the spatial effects of COVID-19 using the spatial panel data model. *Spatial Statistics, 38*, 100443.

Ioannidis, J.P. (2021). Infection fatality rate of COVID-19 inferred from seroprevalence data. *Bulletin of the World Health Organization, 99*(1), 19-33.

Karlsson, M., Ziebarth, N.R. (2018). Population health effects and health-related costs of extreme temperatures: Comprehensive evidence from Germany. *Journal of Environmental Economics and Management*, *91*, 93-117.

Kim, D.D., Goel, A. (2020). Estimating case fatality rates of COVID-19. *The Lancet Infectious Diseases, 20*(7), 773-774.

Krisztin, T., Piribauer, P., & Wögerer, M. (2020). The spatial econometrics of the coronavirus pandemic. *Letters in Spatial and Resource Sciences, 13*(3), 209-218.

LeSage, J.P., Pace, R.K. (2009). *Introduction to Spatial Econometrics.* Boca Raton, FL: Taylor and Francis.

Ma, Y., Zhao, Y., Liu, J., He, X., Wang, B., Fu, S., et al. (2020). Effects of temperature variation and humidity on the death of COVID-19 in Wuhan, China. *Science of the Total Environment*, 724, 138226.

Martinez, M.E. (2018). The calendar of epidemics: seasonal cycles of infectious diseases. *PLoS Pathogene, 14(*11), e1007327.

Michelozzi, P., de'Donato, F., Scortichini, M., Pezzotti, P., Stafoggia, M., De Sario, M., et al. (2020). Temporal dynamics in total excess mortality and COVID-19 deaths in Italian cities. *BMC Public Health, 20*(1), 1-8.

Pesaran, M.H. (2004). *General diagnostic tests for cross-sectional dependence in panels.* IZA Discussion Paper No. 1240. IZA Bonn.

Pesaran, M.H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews, 34*(6-10), 1088-1116.

Shaman, J., Pitzer, V.E., Viboud, C., Grenfell, B.T., Lipsitch, M. (2010). Absolute humidity and the seasonal onset of influenza in the continental United States. *PLoS Biology, 8*(2), e1000316.

Testa, C., Krieger, N., Chen, J., Hanage, W. (2020). *Visualizing the lagged connection between COVID-19 cases and deaths in the United States: An animation using per capita state-level data (January 22, 2020–July 8, 2020).* The Harvard Center for Population and Development Studies (HCPDS) Working Paper 19, no. 4. Cambridge, Massachusetts.

Vanella, P., Wiessner, C., Holz, A., Krause, G., Möhl, A., Wiegel, S., et al. (2020). The role of age distribution, time lag between reporting and death and healthcare system capacity on case fatality estimates of COVID-19. [Preprint] medRxiv. https://doi.org/10.1101/2020.05.16.20104117.

WHO – World Health Organization (2020). *Estimating mortality from COVID-19*. Scientific Brief. https://apps.who.int/iris/bitstream/handle/10665/333642/WHO-2019-nCoV-Sci_Brief-Mortality-2020.1-eng.pdf?sequence=1&isAllowed=y [Last accessed 07 April 2021].

Wilson, N., Kvalsvig, A., Barnard, L.T., Baker, M.G. (2020). Case-fatality risk estimates for COVID-19 calculated by using a lag time for fatality. *Emerging Infectious Diseases, 26*(6), 1339-1341.

Wu, Y., Jing, W., Liu, J., Ma, Q., Yuan, J., Wang, Y., et al. (2020). Effects of temperature and humidity on the daily new cases and new deaths of COVID-19 in 166 countries. *Science of the Total Environment*, 729, 139051.

Zhang, Y., Xu, J., Li, H., Cao, B. (2020). A novel coronavirus (COVID-19) outbreak: a call for action. *Chest, 157*(4), e99-e101.

Appendix

Table A1: Direct effects and spillover effects for temperature, short-run and long-run

		SR Direct	SR Indirect	SR Total	LR Direct	LR Indirect	LR Total
SLX	Mean Temp. t-11				0.007	-0.009	
	Mean Temp t-12				-0.001	-0.002	
	Mean Temp t-13				0.001	0.001	
	Mean Temp t-14				0.003	-0.001	
ND-SDM-FE	Mean Temp t-11				0.003	0.000	0.003
	Mean Temp t-12				-0.003	0.003	0.000
	Mean Temp t-13				0.000	-0.002	-0.002
	Mean Temp t-14				0.000	0.000	0.001
D-SDM-FE	Mean Temp t-11	0.002	-0.000	0.002	0.003	-0.001	0.002
	Mean Temp t-12	-0.004	0.004	0.000	-0.005	0.005	0.000
	Mean Temp t-13	0.001	-0.003	-0.003	0.001	-0.004	-0.003
	Mean Temp t-14	0.000	0.001	0.001	-0.000	0.001	0.001
D-SDM-CSA	Mean Temp t-11	0.001	-0.001	0.000	0.001	-0.001	0.000
	Mean Temp t-12	-0.002	0.003	0.000	-0.002	0.003	0.000
	Mean Temp t-13	0.001	-0.001	-0.000	0.001	-0.001	-0.000
	Mean Temp t-14	0.001	-0.001	0.000	0.001	-0.001	0.000

Notes: Table A1 shows the direct and spillover effect for temperature, in the short-run and long-run for every spatial model from day t-11 to day t-14. The results for day t to day t-10 are omitted for the sake of space, but are available on request. ***p<0.01, **p<0.05, *p<0.1. SLX: Spatial lag of X model; ND-SDM-FE: non-dynamic Spatial Durbin Model with fixed effects; D-SDM-FE: Dynamic Spatial Durbin Model with fixed effects; D-SDM-CSA: Dynamic Spatial Durbin Model with Cross-Sectional Averages; SR: short-run; LR: long-run.

Table A2: Direct effects and spillover effects for intensive care (IC) cases, short-run and long-run

		SR Direct	SR Indirect	SR Total	LR Direct	LR Indirect	LR Total
SLX	IC Cases t-11				-0.039*	0.003*	
	IC Cases t-12				-0.025	0.006***	
	IC Cases t-13				0.060***	0.006***	
	IC Cases t-14				0.007	-0.000	
ND-SDM-FE	IC Cases t-11				-0.045**	-0.027	-0.072**
	IC Cases t-12				-0.011	0.045*	0.034
	IC Cases t-13				0.068***	0.059**	0.126***
	IC Cases t-14				-0.000	-0.076***	-0.076***
D-SDM-FE	IC Cases t-11	-0.045**	-0.024	-0.069**	-0.053**	-0.026	-0.079**
	IC Cases t-12	-0.004	0.051**	0.047	-0.006	0.059**	0.054
	IC Cases t-13	0.073***	0.050**	0.123***	0.086***	0.055*	0.141***
	IC Cases t-14	-0.015	-0.072***	-0.087***	-0.017	-0.083***	-0.100***
D-SDM-CSA	IC Cases t-11	-0.031*	0.001	-0.030	-0.029*	-0.001	-0.030
	IC Cases t-12	-0.020	0.043**	0.023	-0.017	0.041*	0.023
	IC Cases t-13	0.041**	0.028	0.068***	0.038**	0.029	0.068***
	IC Cases t-14	0.003	-0.074***	-0.071***	0.002	-0.072***	-0.070***

Notes: Table A2 shows the direct and spillover effect for intensive care cases, in the short-run and long-run for every spatial model from day t-11 to day t-14. The results for day t to day t-10 are omitted for the sake of space, but are available on request. ***p<0.01, **p<0.05, *p<0.1. SLX: Spatial lag of X model; ND-SDM-FE: non-dynamic Spatial Durbin Model with fixed effects; D-SDM-FE: Dynamic Spatial Durbin Model with fixed effects; D-SDM-CSA: Dynamic Spatial Durbin Model with Cross-Sectional Averages; SR: short-run; LR: long-run.