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The Role of Civic Capital During the Covid-19 Pandemic

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ABSTRACT

We show that civic capital plays an important role when assessing the severity of the COVID-19 pandemic. Analyzing data of a sample of municipalities from the Italian region of Lombardy we provide two new pieces of evidence: (i) the share of vaccinated individuals is higher in municipalities with higher civic capital; (ii) conditional on the severity of the first-wave, municipalities with higher civic capital were less affected in the second wave. Our findings corroborate the idea of civic capital as an important behavioral determinant to curb the spread of Sars-Cov-2.

Introduction

After two years, the negative effects of the COVID-19 pandemic span worldwide. As of the end of January 2022, more than 350 million SARS-CoV-2 infections have been detected, while the number of reported victims passes one million. With the emergence of new variants of concern (VOC), the number of cases across the globe surged, confirming many experts' predictions about the arrival of further waves of infections[1] as for the 1918 Spanish Flu[2]. While further waves may become less and less severe - because of VOC becoming less fatal or, partially, thanks to post-infection immunization[3] - successful health policies against the spread of the pandemic require a massive vaccination campaign. Despite the international and robust evidence that vaccines help in containing the spread of the pandemic, many countries are still experiencing individuals' hesitancy and vaccination rates that are often too low[4]. Understanding the behavioral determinants that explain why vaccination rates are still low may have important policy implications[5,6].

In this paper, we study the relationship between civic capital and municipality-level compliance with COVID-19 vaccination recommendations, conditional on the geographical diffusion of the pandemic. We focus on municipalities of the Italian region of Lombardy, sadly known as the European epicenter, because of the severity and the early start of the first wave in 2020. Our contribution is two-fold. First, we document the existence of a positive and significant relationship between civic capital and vaccination rates. More specifically, municipalities with higher levels of civic capital have a higher level of vaccination rates conditioning on several potential confounding factors such as the local severity of the pandemic. Second, we find a negative relation between the severity of the first-wave of SARS-Cov-2 of in Winter/Spring 2020 and the number of detected infected individuals in the second-wave in Fall 2020. Remarkably, we observe that the reduction in the number of cases is significantly stronger for municipalities with higher levels of civic capital.

Both analyses exploit a traditional regression analysis that allows controlling for potential confounding factors. Results are robust to using of a spatial econometric model that accounts for possible spatial spillovers and cross-municipalities interactions. Overall, we document that civic capital has a central role in explaining the behavior of individuals during the different phases of the COVID crisis.

Our paper contributes to a growing literature connecting social norms and individual behavior such as vaccination decisions or compliance to measures against the spread of infectious diseases[7–14]. Our results are consistent with the idea that civic-minded individuals internalize more than others the effects of their actions on the diffusion patterns of an infectious disease and adapt their behavior accordingly.

Results

Compliance with vaccination

We start by analyzing the relationship between compliance with COVID-19 vaccination recommendations and civic capital across Lombardy municipalities. Vaccines for COVID-19 became available for the public from February 2021 onward, with the elder and more fragile share of the population having priority over other individuals. At the beginning of June 2021, vaccines became available for everyone. To account for the staggered implementation of the policy, we restrict our analysis on the period from June 2021 to October 2021,

To make a starting evaluation of the effect of civic capital on vaccination rates, we graphically compare in Figure 1 the trends of the rates of the vaccinated population for high (top tertile) and low (bottom tertile) civic capital municipalities.

Figure 1 highlights that the two types of municipalities follow a very similar trend during the first three weeks of June. The two trends start diverging after June, become significantly different during the first weeks of July, and remain on two parallel paths until the end of September. This initial descriptive evidence hints at differential compliance with the national vaccination recommendation depending on the level of civic capital.

To provide more robust estimates, we run a set of regressions using the specification of Equation (1). In Table 1 we report the results of these regressions, where the dependent variable is the share of municipal population vaccinated with at least one dose. Each column refers to a different point in time in which this variable is measured. The results are coherent with the initial evidence that high civic capital municipalities have a statistically significantly higher share of vaccinated individuals later in the summer than low civic capital municipalities. The effect size is around 1% of the mean of the dependent variable.

Second-wave number of cases

In this second part, we start by analyzing the geographic distributions of the the second-wave number of cases in relation to first-wave excess mortality. Figure 3 reports for each municipality of Lombardy, the first-wave excess of mortality per 100k inhabitants (left-hand-side panel) and the second-wave cumulative number of positive cases per 100k inhabitants (right-hand-side panel). Even a rough inspection of the maps reveals that the number of second-wave cases is lower in the municipalities that were more severely hit during the first epidemic wave, suggesting that the risk of contagion might be lower in those areas.

To further explore such a phenomenon, we decompose the effect of *First-wave excess mortality* on *Second-wave cases* by accounting for the pre-determined level of *Civic capital*. We do this to disentangle the effect of civic capital from the possible partial immunity obtained by individuals after the first pandemic wave. Existing studies have found association between social capital and health status[15]. Moreover, recent research has highlighted the role of civic capital in slowing down the spread of COVID-19. In particular,[16,17] investigate the impact of civic culture on social distancing behavior and, indirectly, on the spread of COVID-19 finding that areas with higher levels of civic capital reduced their mobility earlier and more than others.

Formally, our empirical investigation consists in estimating a simplified version of equation (1), where we use an ordinary least-squares regressions with the number of COVID-19 cases per 100k inhabitants detected during the second wave (*Second-wave cases*) as the dependent variable and the excess of mortality per 100k inhabitants observed during the first wave (*First-wave excess mortality*) as the main explanatory variable. OLS estimates are reported in Appendix in Table 3. We report in columns (1)-(5) robust standard errors and, in column (6), Conley corrected standard errors. The excess-mortality coefficient has a negative sign, and it is statistically significantly different from zero at 5% level. The standardized coefficient of *First-wave excess mortality* suggests that an increase of one standard deviation of the first-wave excess mortality corresponds approximately to a 30% reduction of detected second-wave cases. This relationship is robust to the inclusion of a minimal set of demographic controls such as population density (*Population density*), the share of individuals older than 60 (*Share of over 60*), a proxy of air pollution (*Pollution*), and our proxy of civic capital (*Civic capital*) that we have used in the previous analysis.

One possible explanation for the observed negative relation between the first-wave severity and the second-wave reduced risk of contagion is that people living in areas that were severely affected during the first-wave are likely to have changed their behavior in a way that would make less likely the spread of the virus (e.g., more accurate use of protecting devices, more frequent sanitizing procedures, etc.). Still, severe exposure to the virus during the first-wave may have immunized a large share of the population, contributing to a much slower spread of the virus during the second wave of the epidemic. Regardless of the actual mechanism driving the negative relation our main interest is about the role of civic capital in mediating the effect.

In Figure 2 we shows the estimated coefficients of an OLS regression following the full specification of equation (1), therefore including the interactions between *First-wave excess mortality* and the tertiles of *Civic capital*. The coefficients are all negative, statistically significant, and increasing in magnitude. This implies that keeping fixed the severity of the first wave, municipalities belonging to the first tertile of the distribution did significantly worse than those belonging to the other tertiles. This finding confirms the intuition that the observed negative relation between the severity of the first-wave of the epidemic and the number of the second-wave cases is stronger for municipalities with higher levels of civic capital. These results are consistent with the idea that civic-minded individuals internalize more than others the effect of their behavior on spreading an infectious disease.

As an additional check we control for possible spatial effects and cross-municipalities interactions[18]. There is no reason to believe that infections and contagions follow the administrative boundaries of municipalities. Omitting to take them into account may reduce the efficiency of our estimates and bias them. To address this issue, we estimate a spatial model using the generalized spatial two-stage least squares (GS2SLS) estimator of[19]. We report in Table 4 the results of spatial estimations of the correlation between first-wave excess mortality and second-wave cases, which reproduces the same specification of column 5 of 3. We employ a contiguity matrix, and we implement a spatial autoregressive model (column (1)), a spatial error model (column (2)), and a model that combines the two by considering both a spatial lag and a spatial error structure (column (3)). Allowing for a spatial structure in our data does not alter our baseline estimates: the coefficient of *First-wave excess mortality* is negative and statistically significant at 1%.

Discussion

We study the relationship between the exposure to the first-wave COVID-19 pandemic in Lombardy and the current second-wave risk of contagion. We find that municipalities more severely hit by the epidemic during the first wave are experiencing fewer cases during the second wave. Importantly, we provide empirical evidence that this negative effect is stronger in municipalities with an high level of civic capital. These results are in line with the hypothesis that behavioral response play a crucial role in virus diffusion, along with a partial immunization of the local population. Although the results should be interpreted cautiously in light of the assumptions and limitations inherent to our approach, our results suggest that policymakers and health authorities should collaborate to design containment measures that are tailored only on small geographic entities.

Materials and methods

Data

Civic capital To study the role of civic capital in the spread of the pandemic, we combine three proxies of civic capital commonly used in the literature (organ donations, share of urban solid waste recycling, and tax compliance), which we aggregate via principal component analysis. We use the first principal component of the three variables as our measure of civic capital, where the principal component explains 45.5% of the variance (see Appendix for the pairwise correlations between the principal component and the three proxies of civic capital).

This variable is pre-determined with respect to the pandemic. The presence of an organ donation association is taken from the association website and refers to 2014 (see http://www.aido.it). The share of urban solid waste recycling measures the 2014-2017 average share of recycling over the total amount of urban waste produced, and it is taken from the Italian National Statistical Institute (ISTAT), available at http://amisuradicomune.istat.it/aMisuraDiComune/. Data for the tax compliance rate were obtained from Italy's national public broadcasting company (RAI - Radiotelevisione Italiana) and are available for the period 2004-2010. The resulting measure of civic capital *Civic Capital* variable captures the propensity of individuals to contribute to public good and to comply with legal and social norms.

Vaccines Our primary variable of interest is a measure of vaccine compliance. This variable accounts for the number of vaccinated individuals for each municipality in Lombardy from May 1 to September 1 2021.We gather data from the Lombardy Region (available at https://hub.dati.lombardia.it/). This variable is used in section *Results* to estimate the effect of civic capital on vaccination compliance in 2021.

Excess mortality To measure the pandemic severity at the municipality-level, we use excess mortality defined as the difference between the number of deaths observed in Lombardy during the first COVID-19 wave (between January 1 and May 31, 2020), and the average number of deaths observed during the same time-span for all the years between 2015 and 2019[20]. We gather mortality data released on October 22, 2020 by ISTAT, available at https://www.istat.it/it/archivio/240401. The dataset includes the total mortality of 1,501 out of the 1,506 municipalities of Lombardy, virtually covering the entire regional population. We merge this information with data on the number of new cases observed during the second COVID-19 wave, from September 1 to November 1, 2020. We obtained data from the Lombardy Region, which are available at https://datawrapper.dwcdn.net/iMArO/12/ and https://www.datawrapper.de/_/567DW/.

Other control variables We also collect information on the age structure of the population and compute the share of individuals over 60 years (*Share of over 60*) from ISTAT, and an indicator of the air quality (*Pollution*) based on the prevalence of fine particulate matters PM 2.5 over the period 2017 to 2019 (*Pollution*) collected from ARPA Lombardia (Regional Environmental Protection Agency).

Data availability The datasets used and analysed during the current study are publicly available on the ICPSR open repository at https://www.openicpsr.org/openicpsr/project/166041/version/V1/view.

Methods

In results section we analyze our dataset using both ordinary least-squares (OLS) and generalised spatial two stage least squares (GS2SLS) estimator of[19]. Moreover, in our OLS regression we account for spatial correlation across nearby units using Conley standard errors[21]. Specifically, we estimate the following model

$$y_{it} = \alpha + \beta \mathbf{CC}_i + \gamma \mathbf{Z}_i + \varepsilon_i \tag{1}$$

where, for each municipality i at time t, y is the share of vaccinated individuals at different points in time, and **CC** are a set of dummy variables denoting civic capital tertiles. **Z** is a set of control variables that we use to account for possible confounding factors that may affect the interpretation of our findings, that include the excess mortality per 100k inhabitants observed during the first epidemic wave, the the second-wave number of detected cases, the share of population over 60, and an indicator of air quality. Finally, α is the constant, and ε is a disturbance term.

We confirm that all methods were carried out in accordance with relevant guidelines and regulations.

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Author contributions statement

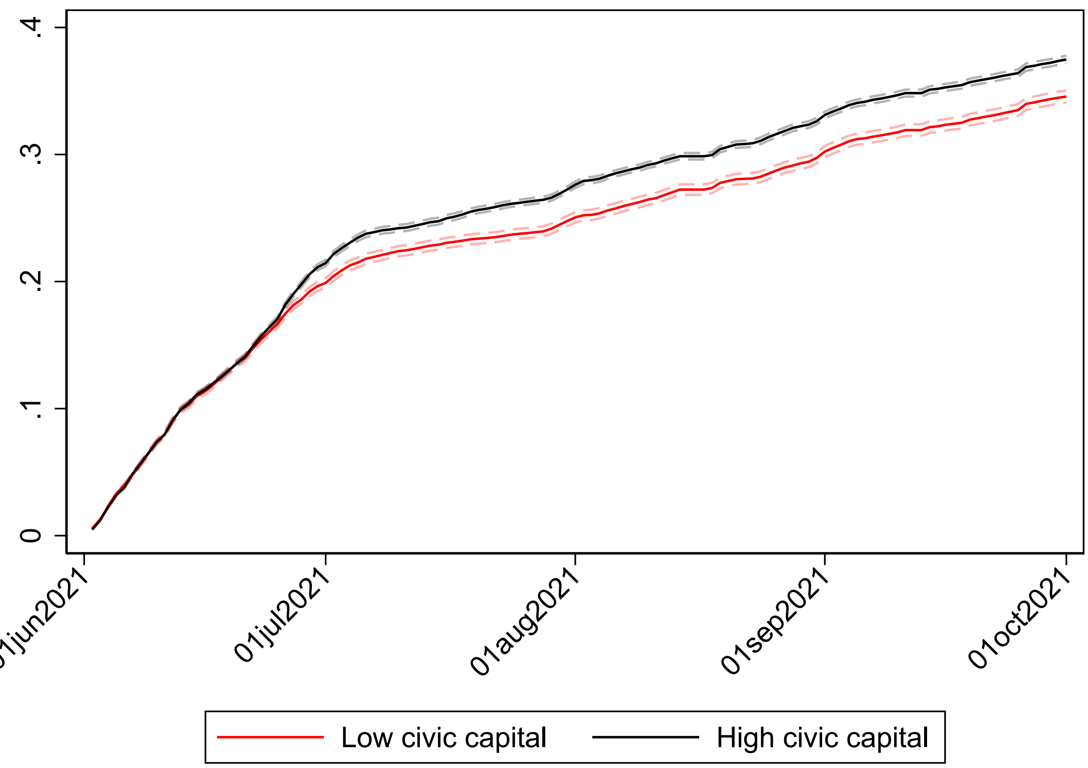
The authors contributed equally to this research.

Additional information

The authors do not have competing interests.

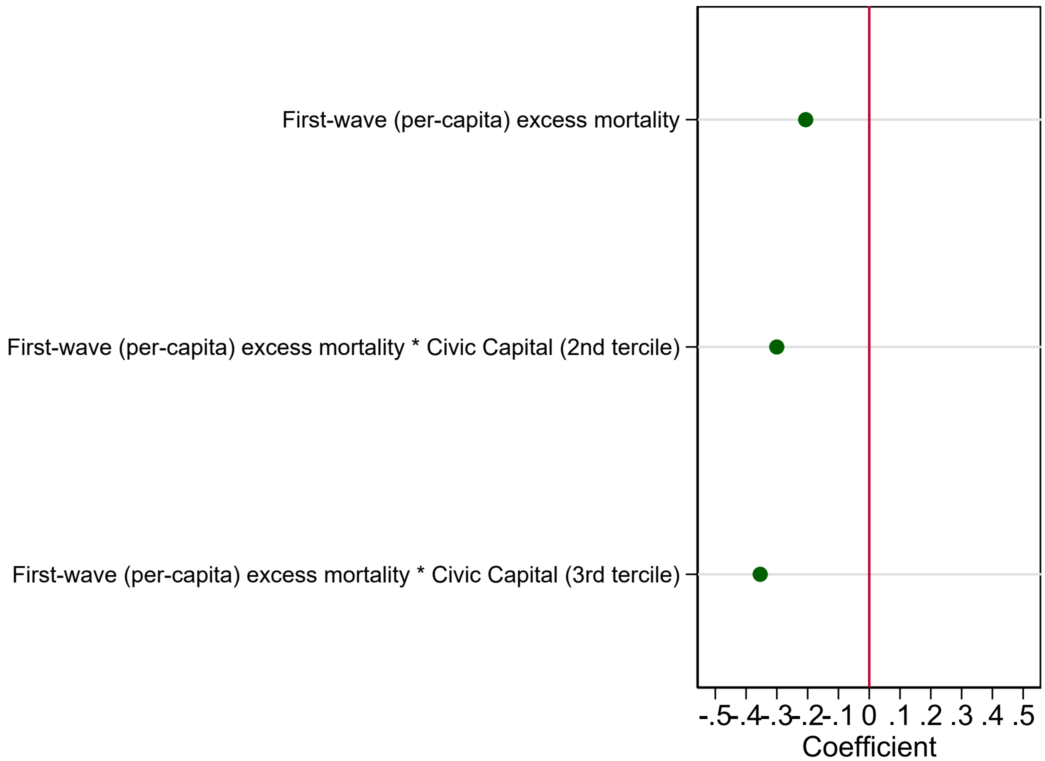
Appendix

Figure 1. Covid19 vaccination rates (first dose), by municipality type



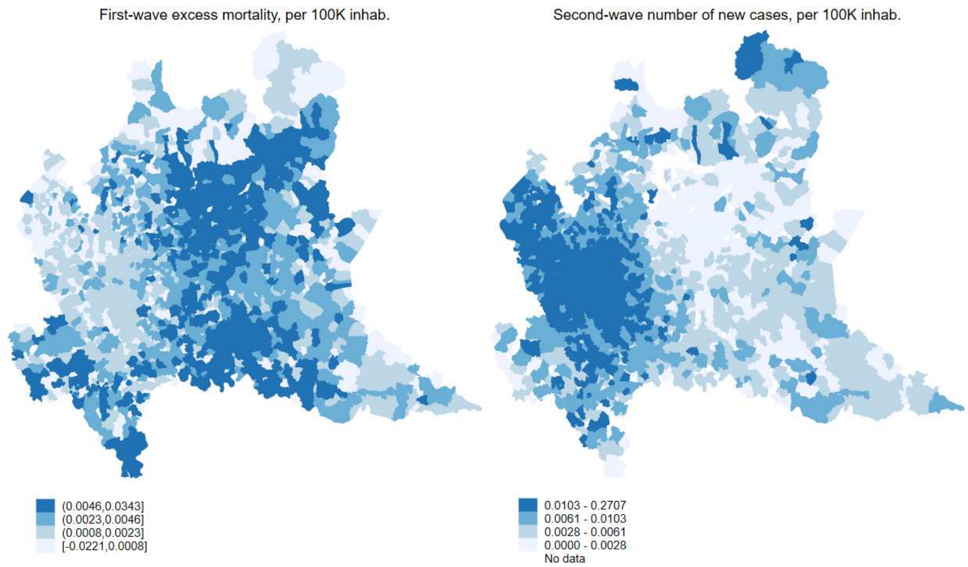
Note: This figure shows the average growth of vaccination rate over time for municipalities with low and high civic capital from June 1, 2021 to October 1, 2021. Solid lines represent the mean value. Dashed lines define the 95 percent confidence interval.

Figure 2. Regression coefficients of civic capital and excess mortality



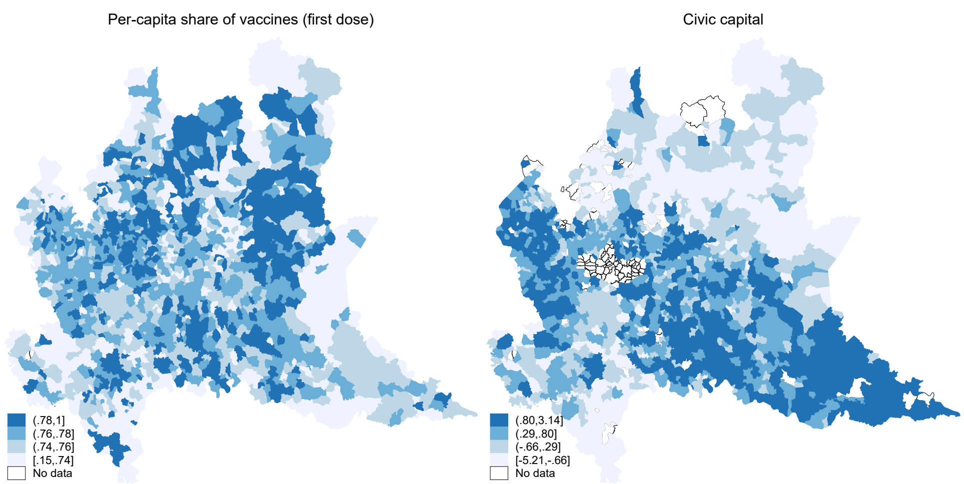
Notes: The figure shows the stand-alone and interacted coefficients of the regression model (5) of Table 3, to which we added the interaction between the distribution tertiles of *Civic capital* and *First-wave excess mortality*.

Figure 3. Geographic distribution of first vs second COVID19 waves



Notes: The figure shows the geographic distribution of the first-wave excess of mortality (left-hand-side panel) and the second-wave cumulative number of positive cases (right-hand-side panel).

Figure 4. Geographic distribution of per-capita vaccines vs civic capital



Notes: The figure shows the geographic distribution of per-capita vaccines (left-hand-side panel) and our measure of civic capital (right-hand-side panel).

Table 1. Vaccine estimates

Dep. Variable: Vaccination rate	1st July (1)	1st August (2)	1st September (3)	1st October (4)
High Civic capital	0.002	0.009***	0.013***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
Mean Vaccination rate	0.609	0.666	0.722	0.763
N observations	934	934	934	934
R^2	0.768	0.724	0.654	0.540
S.E.	Robust	Robust	Robust	Robust

Notes: This table reports ordinary least-squares regressions. The dependent variable is *vaccination rate* at the day specified in column head. The main explanatory variable is *High Civic capital*, which identified municipalities belonging to the third tertile of the underling civic capital proxy. Additional controls include: the share of vaccinated individuals at the first of June, the excess of mortality observed during the first wave per 100k inhabitants (*first-wave excess mortality*), second-wave cumulative number of positive cases (*second-wave cases*), the share of individuals over 60 years (*share of over 60*), an indicator of the air quality (*Pollution*) based on the prevalence of fine particulate matters PM 2.5 over the period 2017 to 2019. The sample do no include municipalities in second tertile of the distribution of civic capital. The regressions are weighted by population. Robust standard errors are presented in parentheses. *, ** and *** denote rejection of the null hypothesis of the coefficient being equal to 0 at 10%, 5% and 1% significance level, respectively.

Table 2. Civic Capital components, pairwise correlations

	Civic Capital	Solid waste Recycling	Tax Compliance	Organ Donation Association
Civic Capital	1			
Solid Waste Recycling	0.796***	1		
Tax Compliance	0.819***	0.350***	1	
Organ Donation Association	0.252***	0.0227***	0.0913***	1

Table 3. OLS estimates

Dep. Variable: Second-wave cases	(1)	(2)	(3)	(4)	(5)	(6)
First-wave excess mortality	-0.6455**	-0.5967**	-0.5984**	-0.6138**	-0.6153**	-0.6369**
	(0.2531)	(0.2544)	(0.2621)	(0.2679)	(0.2704)	(0.2781)
Population density		0.2351***	0.2344***	0.2102***	0.2110***	0.2090***
		(0.0177)	(0.0167)	(0.0205)	(0.0206)	(0.0369)
Share of over 60			0.0958	4.8741	5.1981	5.3448
			(4.9032)	(6.5172)	(6.9296)	(9.6926)
Pollution				12.1499*	11.3421*	11.5993
				(6.5179)	(5.9557)	(8.7915)
Civic capital					0.3636	0.4580
					(1.1460)	(2.0478)
Observations	1,501	1,499	1,489	1,480	1,465	1,454
R^2	0.0892	0.1348	0.1347	0.1373	0.1375	0.1385
S.E.	Robust	Robust	Robust	Robust	Robust	Conley

Notes: This table reports ordinary least-squares regressions. The dependent variable is *Second-wave cases*, the COVID-19 cases per 100k inhabitants detected during the second wave. The main explanatory variable is *First-wave excess mortality* the excess of mortality observed during the first wave per 100k inhabitants. Controls include: (i) the share of individuals over 60 years (*Share of over 60*); (ii) an indicator of the air quality (*Pollution*) based on the prevalence of fine particulate matters PM 2.5 over the period 2017 to 2019 (*Pollution*) and (iii) a proxy of a municipality civic capital, that is the share of recycling of urban solid waste (*Civic capital*). Robust standard errors are presented in parentheses. *, ** and *** denote rejection of the null hypothesis of the coefficient being equal to 0 at 10%, 5% and 1% significance level, respectively. In column 6, standard errors are computed using Conley standard errors ([21]).

Table 4. Spatial estimates

Dep. Variable: Share of vaccines	(1)	(2)	(3)
Civic Capital	0.0065***	0.0081***	0.0077***
	(0.0018)	(0.0019)	(0.0019)
Second wave per capita cases	0.1069	-0.1325	-0.1029
	(0.2426)	(0.2442)	(0.2443)
First-wave excess mortality	1.2163***	0.7907***	0.8430***
	(0.3265)	(0.2934)	(0.2933)
Population density	0.0000***	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Pollution	-0.0019***	-0.0010*	-0.0013**
	(0.0004)	(0.0005)	(0.0006)
Share of over60	0.4912***	0.5685***	0.5615***
	(0.0308)	(0.0304)	(0.0305)
λ	0.0833		-0.0427
	(0.0144)		(0.0789)
ρ		0.5518***	0.5762***
		(0.0392)	(0.0503)
Observations	1,401	1,401	1,401

Notes: This table presents the results of a spatial model estimated using the generalized spatial two-stage least squares (GS2SLS) estimator of[19]. Included controls are the same as in the specification of column 5 of Table 3. We employ a contiguity matrix. A spatial lag model, a spatial error model, and a model that combines the two by considering both a spatial lag and a spatial error structure are respectively presented in columns (1), (2), and (3). λ is the spatial lag term, while ρ is the spatial error. The dependent variable is *Share of vaccines* recorded in June 2021. The main explanatory variable is *Civic Capital*. Controls variables include the number of second wave per-capita COVID19 cases, the first-wave per-capita excess mortality, the population density, the share of individuals over 60 years, an indicator of the air quality based on the prevalence of fine particulate matters PM 2.5 over the period 2017 to 2019. Robust standard errors are presented in parentheses. *, ** and *** denote 10%, 5% and 1% significance level, respectively.