A Data Appendix

Table A.1: Definition of variables and data sources

	year	description	source
Panel A – Outcomes			
Austria: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the municipality-week level. We normalize this variable with population numbers from Statistics Austria.	Electronic Epidemiological Reporting System (EMS) provided by the Federal Ministry of Social Affairs, Health, Care and Consumer Protection; Statistics Austria
Germany: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the county-day level. We normalize this variable with population numbers from the Statistical Offices of the German States.	Robert-Koch Institute; Statistical Offices of the German States
Great Britain: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the lower tier local authority-day level. For England, this level corresponds to Non-Metropolitan Districts, Unitary Authorities, Metropolitan Districts and London Boroughs. Two very small authorities are added to larger authorities due to privacy concerns (City of London to Hackney and Isles of Scilly to Cornwall). We aggregate the data accordingly. For Wales, the lower tier local authorities corresponds to the Unitary Authorities. For Scotland, the lower tier local authorities corresponds to the Council Areas. We normalize this variable with population numbers from the Office of National Statistics (ONS).	Public Health Boards of England, Scotland and Wales; ONS
Great Britain: cumulative excess deaths per 100,000 inhabitants	2015 - 2020	The number of deaths recorded from January to June 2020 minus the average number of deaths on the same week in the period from 2015 to 2019 at the lower tier local authority-week level. The data are provided in the 2020 boundaries (South Bucks, Chiltern, Wycombe and Aylesbury Vale are aggregated up to Buckinghamshire). Weekly data are only available for England and Wales. We normalize this variable with population numbers from the ONS.	ONS
Italy: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the province-day level. We normalize this variable with population numbers from ISTAT.	Italian Department of Civil Protection; ISTAT
Italy: cumulative excess deaths per 100,000 inhabitants	2015 - 2020	The number of deaths recorded from January 1, 2020 to June 30, 2020 minus the average number of deaths on the same day in the period from 2015 to 2019 at the municipality-day level. We normalize this variable with population numbers from ISTAT.	ISTAT
Netherlands: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the municipality-day level. We normalize this variable with population numbers from Statistics Netherlands.	National Institute for Public Health and the Environment; Statistics Netherlands
Netherlands: cumulative excess deaths per 100,000 inhabitants	2019 - 2020	The number of deaths recorded from January to June 2020 minus the average number of deaths on the same week in the period in 2019 at the municipality-week level. We normalize this variable with population numbers from Statistics Netherlands.	Statistics Netherlands
Sweden: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the municipality-week level. Values with less than 15 cases are censored. Therefore, we impute these values by assuming a log-linear functional form. We normalize this variable with population numbers from Statistics Sweden.	Public Health Agency of Sweden; Statistics Sweden
Sweden: cumulative excess deaths per 100,000 inhabitants	2015 - 2020	The number of deaths recorded from January to June 2020 minus the average number of deaths in the period from 2015 to 2019 at the municipality-month level normalized by population numbers from Statistics Sweden. We also obtained data in 10-day blocks for the years 2018 to 2020.	Statistics Sweden
Switzerland: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the municipality-day level. We normalize this variable with population numbers from the Swiss Federal Statistical Office.	Swiss Federal Office of Public Health (FOPH); Swiss Federal Statistical Office
Panel B – Independent Variables			
Austria: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the municipality level.	Austrian Ministry of the Interior
Germany: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the county level.	Statistical Offices of the German States
Germany: associations per 1,000 inhabitants	2008	Number of associations normalized by the number of inhabitants at the county level.	Franzen and Botzen (2011)
Great Britain: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the lower tier local authority level.	House of Commons Library
Great Britain: blood donations per capita	2015-2019	Average number of blood donations per capita in the period from 2015 to 2019 as reported by the NHS at the lower tier local authority level.	NHS

continued

Table A.1 continued

	year	description	source
Italy: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the province level.	Department of Internal Affairs
Italy: blood donations per capita	2017	Whole blood and plasma donations per capita as reported by AVIS, the Italian association of voluntary blood donors. This variable is only available for 103 of the 107 provinces (Belluno, Gorizia, Imperia and Lucca are missing).	AVIS
Italy: literacy rate	1821	The literacy rate for the total population (men and women combined) in 1821. The data are only available in the 1911 province boundaries. We drop the modern provinces of Bolzano, Trento, Gorizia and Trieste since they were not part of Italy in 1911. We also exclude the modern provinces of Varese, Frosinone, Rieti, Pescara, Latina, Nuoro and Enna because it is not straightforward to match the historical data to the new jurisdictions.	Ciccarelli and Weisdorf (2018)
Netherlands: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the municipality level.	Dutch Electoral Council
Netherlands: registered organ donors per capita	2020	Number of registered organ donors willing to donate as of March 2020, relative to population above 12 years of age at the municipality level.	National Institute for Public Health and the Environment
Sweden: turnout	2019	Turnout to the 2019 European Parliament Election held at the end of May 2019 at the municipality level.	Swedish Election Authority
Switzerland: turnout	2019	Turnout to the 2019 national elections at the municipal level.	Swiss Federal Statistical Office
Panel C − Control Variables			
Austria: hospital beds per 1,000 inhabitants	2019	The number of hospital beds at the municipality level normalized with population numbers from Statistics Austria.	Federal Ministry of Social Affairs, Health, Care and Consumer Protection
Austria: share educated	2010	The share of the population at the municipality level that has completed a university degree.	Statistics Austria
Austria: share white-collar	2010	The share of working population at the municipality level that is employed in white-collar sectors.	Statistics Austria
Austria: GDP per capita	2017	Gross domestic product per inhabitant at current prices at the NUTS-3 level.	Statistics Austria
Austria: share old	2019	The share of the population at the municipality level that is older than 65 years of age.	Statistics Austria
Austria: population density	2019	The number of inhabitants per square kilometer at the municipality level.	Statistics Austria
Germany: hospitals per 100,000 inhabitants	2017	The number of hospitals at the county level normalized with population numbers from the Statistical Offices of the States.	Statistical Offices of the States
Germany: share educated	2011	The share of the population at the county level that has completed at least high-school.	Census
Germany: share white-collar	2019	The share of working population at the county level that is employed in a white-collar sector.	Statistical Offices of the States
Germany: GDP per capita	2017	Gross domestic product per inhabitant at current prices at the county level.	Statistical Offices of the States
Germany: share old	2017	The share of the population at the county level that is older than 65 years of age.	Statistical Offices of the States
Germany: population density	2019	The number of inhabitants per square kilometer at the county level.	Statistical Offices of the States
Great Britain: hospitals per 100,000 inhabitants	2019	The number of hospitals at the lower tier local authority level normalized with population numbers from the Office of National Statistics.	NHS websites
Great Britain: share educated	2011	The share of the population at the NUTS-2 level that has at least a tertiary degree.	OECD
Great Britain: share white-collar	2011	The share of working population at the lower tier local authority level that is employed in a white-collar sector.	Census
Great Britain: GDP per capita	2018	Gross domestic product per inhabitant at current prices converted into Euros at the lower tier local authority level.	Office of National Statistics
Great Britain: share old	2019	The share of the population that is older than 65 years of age at the lower tier local authority level.	Office of National Statistics
Great Britain: population density	2019	The number of inhabitants per square kilometer at the lower tier local authority level.	Office of National Statistics
Italy: hospitals per 100,000 inhabitants	2019	The number of hospitals at the province (municipality) level normalized with population numbers from ISTAT.	ISTAT
Italy: share educated	2011	The share of the population at the province (municipality) level that has completed at least some college education.	Census
Italy: share white-collar	2017	The share of working population at the province level that is employed in a white-collar sector.	OECD
Italy: GDP per capita	2017	Gross domestic product per inhabitant at current prices at the province level.	ISTAT
Italy: taxable income per capita	2018	The municipal tax base of the national income tax divided by the number of inhabitants.	Italian Fiscal Agency
Italy: share old	2011	The share of the population at the province (municipality) level that is older than 65 years of age.	Census
Italy: population density	2019	The number of inhabitants per square kilometer at the province (municipality) level.	ISTAT
Netherlands: hospitals per 100,000 inhabitants	2019	The number of hospitals at the municipality level normalized with population numbers from Statistics Netherlands.	National Institute for Public Health and the Environment

continued

Table A.1 continued

	year	description	source
Netherlands: share educated	2017	The share of the population at the municipality level that has completed least some college education.	Statistics Netherlands
Netherlands: share white-collar	2019	The share of working population at the municipality level that is employed in a white-collar sector.	Statistics Netherlands
Netherlands: income per capita	2018	Average income per inhabitant at the municipality level.	Statistics Netherlands
Netherlands: share old	2019	The share of the population at the municipality level that is older than 65 years of age.	Statistics Netherlands
Netherlands: population density	2019	The number of inhabitants per square kilometer at the municipality level.	Statistics Netherlands
Sweden: share old	2019	The share of the population at the municipality that is older than 65 years of age.	Statistics Sweden
Sweden: population density	2019	The number of inhabitants per square kilometer at the municipality level.	Statistics Sweden
Sweden: hospitals per 100,000 inhabitants	2019	The number of hospital beds at the municipality level normalized with population numbers from Statistics Sweden.	Statistics Sweden
Sweden: share white-collar	2018	The share of working population at the municipality level that is employed in a white-collar sector.	Kolada
Sweden: GPD per capita	2017	Gross domestic product per inhabitant at current prices converted into Euros at the municipality level.	Kolada
Sweden: share educated	2019	The share of the population at the municipality level that has completed least high school.	Statistics Sweden
Switzerland: hospitals per 100,000 inhabitants	2018	The number of hospitals at the municipality level normalized with population data from the Swiss Federal Statistical Office.	Swiss Federal Office of Public Health (FOPH)
Switzerland: share educated	2016-2018	The share of the population at the district (Bezirk) level that has completed high-school.	Swiss Federal Statistical Office
Switzerland: taxable income per capita	2016	Average taxable income per capita at current prices converted into Euros at the municipality level.	Swiss Federal Statistical Office
Switzerland: share old	2019	The share of the population at the municipality level that is older than 65 years of age.	Swiss Federal Statistical Office
Switzerland: population density	2019	The number of inhabitants per square kilometer at the municipality level.	Swiss Federal Statistical Office

Notes: This table provides details on the definition and sources for all variables used.

Table A.2: Summary statistics

	mean	p25	p75	sd	min	max	N
Austria: municipality level							
turnout	0.54	0.47	0.60	0.08	0.24	0.84	2095
population (in 100,000)	0.04	0.01	0.03	0.43	0.00	19.11	2095
population density (in 1,000/km^2)	0.14	0.04	0.13	0.27	0.00	4.60	2095
GDP per capita (in 1,000€)	37.01	29.60	44.60	8.71	23.00	54.50	2095
hospital beds per 1,000 inhabitants	3.50	0.00	0.00	20.86	0.00	408.72	2095
share white-collar	0.18	0.14	0.21	0.05	0.04	0.36	2095
share old	0.20	0.17	0.22	0.04	0.10	0.40	2095
share educated	0.31	0.27	0.35	0.06	0.13	0.62	2095
Germany: county level							
turnout	0.61	0.57	0.64	0.05	0.48	0.74	401
associations per 1,000 inhabitants	6.88	5.67	7.81	1.97	1.00	17.34	401
population (in 100,000)	2.07	1.04	2.42	2.48	0.34	37.54	401
population density (in 1,000/km^2)	0.43	0.09	0.52	0.57	0.03	3.91	401
GDP per capita (in 1,000€)	37.16	27.93	40.51	16.12	16.40	172.43	401
hospitals per 100,000 inhabitants	2.48	1.50	3.06	1.50	0.00	9.80	401
share white-collar	0.43	0.35	0.49	0.10	0.22	0.76	401
share old	0.22	0.20	0.24	0.03	0.16	0.32	401
share educated	0.32	0.27	0.38	0.09	0.12	0.58	401
Great Britain: lower tier local authority level							
turnout	0.37	0.34	0.40	0.05	0.23	0.54	369
blood donors per capita	0.01	0.01	0.02	0.01	0.00	0.03	369
population (in 100,000)	1.76	1.01	2.15	1.19	0.22	11.42	369
population density (in 1,000/km^2)	1.60	0.20	2.05	2.49	0.01	16.24	369
GDP per capita (in 1,000€)	33.55	23.48	36.77	24.75	15.40	309.99	369
hospitals per 100,000 inhabitants	1.17	0.00	1.47	1.51	0.00	11.23	369
share white-collar	0.18	0.14	0.22	0.07	0.08	0.50	369
share old	0.22	0.20	0.23	0.02	0.16	0.31	369
share educated	0.43	0.37	0.46	0.08	0.32	0.72	369
Italy: province level							
turnout	0.56	0.50	0.65	0.11	0.34	0.70	107
blood donations per capita	0.04	0.02	0.05	0.02	0.00	0.12	103
literacy rate in 1821	0.25	0.16	0.35	0.11	0.09	0.54	69

continued

Table A.2 continued

	mean	p25	p75	sd	min	max	N
population (in 100,000)	5.64	2.35	6.22	6.17	0.84	43.42	107
population density (in 1,000/km^2)	0.27	0.11	0.28	0.38	0.04	2.63	107
GDP per capita (in 1,000€)	23.51	16.95	28.25	6.66	12.89	48.69	107
hospitals per 100,000 inhabitants	1.79	1.30	2.25	0.69	0.47	4.00	107
share white-collar	0.34	0.31	0.37	0.04	0.25	0.47	107
share old	0.24	0.22	0.25	0.02	0.18	0.29	107
share educated	0.10	0.09	0.11	0.02	0.06	0.16	107
Netherlands: municipality level							
turnout	0.42	0.38	0.47	0.07	0.26	0.80	355
organ donors per capita	0.26	0.24	0.29	0.04	0.10	0.35	355
population (in 100,000)	0.49	0.21	0.50	0.72	0.01	8.63	355
population density (in 1,000/km^2)	0.88	0.24	1.16	1.05	0.02	6.62	355
income per capita (in 1,000€)	32.25	29.70	33.80	4.22	24.90	58.60	355
hospitals per 100,000 inhabitants	1.33	0.00	2.28	1.80	0.00	8.97	355
share white-collar	0.18	0.15	0.20	0.03	0.10	0.32	355
share old	0.22	0.20	0.24	0.03	0.10	0.33	355
share educated	0.17	0.13	0.18	0.08	0.05	0.73	355
Sweden: municipality level							
turnout	0.52	0.48	0.56	0.06	0.35	0.74	290
population (in 100,000)	0.36	0.10	2.31	0.74	0.02	9.74	290
population density (in 1,000/km^2)	0.16	0.01	0.08	0.58	0.00	6.03	290
GDP per capita (in 1,000€)	34.97	25.99	39.32	14.85	14.25	167.56	290
hospitals per 100,000 inhabitants	0.61	0.00	0.00	1.59	0.00	16.89	290
share white-collar	0.29	0.23	0.33	0.08	0.15	0.60	290
share old	0.24	0.21	0.27	0.04	0.13	0.36	290
share educated	0.78	0.76	0.81	0.04	0.68	0.87	290
Switzerland: municipality level							
turnout	0.47	0.42	0.51	0.08	0.23	0.85	2201
population (in 100,000)	0.04	0.01	0.04	0.13	0.00	4.20	2201
population density (in 1,000/km^2)	0.44	0.08	0.47	0.79	0.01	12.81	2201
taxable income per capita (in 1,000€)	30.19	24.22	32.38	13.46	5.17	388.72	2201
hospitals per 100,000 inhabitants	5.38	0.00	0.00	30.70	0.00	609.76	2201
share old	0.19	0.16	0.22	0.04	0.06	0.40	2201
share educated	0.48	0.43	0.53	0.06	0.30	0.59	2201
Italy: municipality level							
turnout	0.59	0.48	0.71	0.15	0.12	1.00	7903
population (in 100,000)	0.08	0.01	0.06	0.43	0.00	28.56	7903
population density (in 1,000/km^2)	0.30	0.04	0.28	0.65	0.00	12.22	7903
taxable income per capita (in 1,000€)	12.65	9.77	15.03	3.31	3.04	35.45	7903
hospitals per 100,000 inhabitants	0.80	0.00	0.00	5.39	0.00	235.85	7903
share old	0.29	0.25	0.32	0.06	0.09	0.69	7903
share educated	0.07	0.05	0.09	0.03	0.00	0.27	7903

Notes: Blood donations per capita are missing for 4 (Belluno, Gorizia, Imperia and Lucca) out of 107 provinces. The literacy rate in 1821 refers to the province boundaries of 1911 when only 69 provinces existed.

Table A.3: Geographical units across countries

Covid-19 cases				
country	micro-area (NUTS-3 or lower)	# micro-areas	region (NUTS-1)	# regions
Austria	municipality (*Gemeinde*)	2095	group of States (*Bundesland*)	3
Germany	county (*Kreis*)	401	State (*Bundesland*)	16
Great Britain	lower tier local authority	369	Wales, Scotland and statistical regions of England	11
Italy	province (*Province*)	107	group of Regions (*Regioni*)	5
Netherlands	municipality (*Gemeente*)	355	Land (*Landsdeel*)	4
Sweden	municipality (*Sveriges kommuner*)	290	Land (*Landsdelar*)	3
Switzerland	municipality (*Gemeinde*)	2201	canton (*Kanton*) (NUTS-3)	26
Excess deaths				
country	micro-area (below NUTS-3)	# micro-areas	region (NUTS-3)	# regions
Great Britain	lower tier local authority	334	Wales and statistical regions of England (NUTS-1)	10
Italy	municipality (*commune*)	7903	province (*Province*)	107
Netherlands	municipality (*Gemeente*)	355	COROP regions (*COROP-gebieden*)	40
Sweden	municipality (*Sveriges kommuner*)	290	county (*Län*)	21

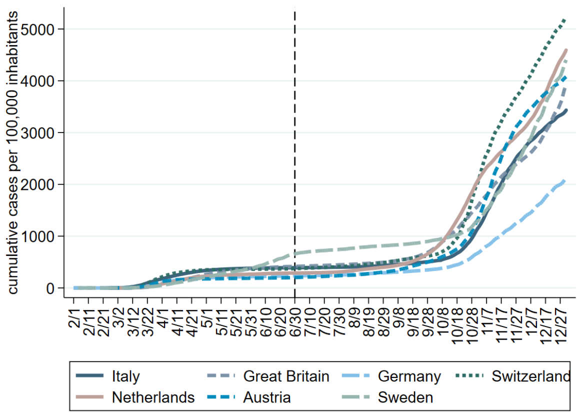
Notes: This table provides an overview about the different geographical units within each country. The column “region” for Covid-19 cases refers to the NUTS-1 level. In Switzerland, where the NUTS-1 region corresponds to the whole country, we add an additional robust check where we use the cantons (the NUTS-3 level) as the region. The column “region” for the cases robustness checks and excess deaths refers to the NUTS-3 level, except for Great Britain, where the micro-area corresponds to the NUTS-3 level. Hence, we are using the NUTS-1 level as regions for Great Britain. Since weekly deaths data are not available for Scotland, the number of micro-areas drops to 334 and the number of region drops to 10 for Great Britain.

Table A.4: Timing of pandemic-related events and policy responses

country	**ban of gatherings**	**school closure**	**lockdown during 1st wave**	**lockdown light during 2nd wave**	**lockdown during 2nd wave**
Italy	Feb. 23	Mar. 4	Mar. 9	-	Nov 4
Austria	Mar. 10	Mar. 10	Mar. 16	Nov. 3	Nov. 17
Germany	Mar. 8	Mar. 16	Mar. 23	Nov. 2	Dec- 16
Netherlands	Mar. 12	Mar. 15	Mar. 23	Oct. 14	Dec. 15
Sweden	Mar. 11	-	-	-	-
Switzerland	Feb. 28	Mar. 13	Mar. 16	-	Oct. 28
Great Britain	Mar. 23	Mar. 18	Mar. 23	-	Nov. 5

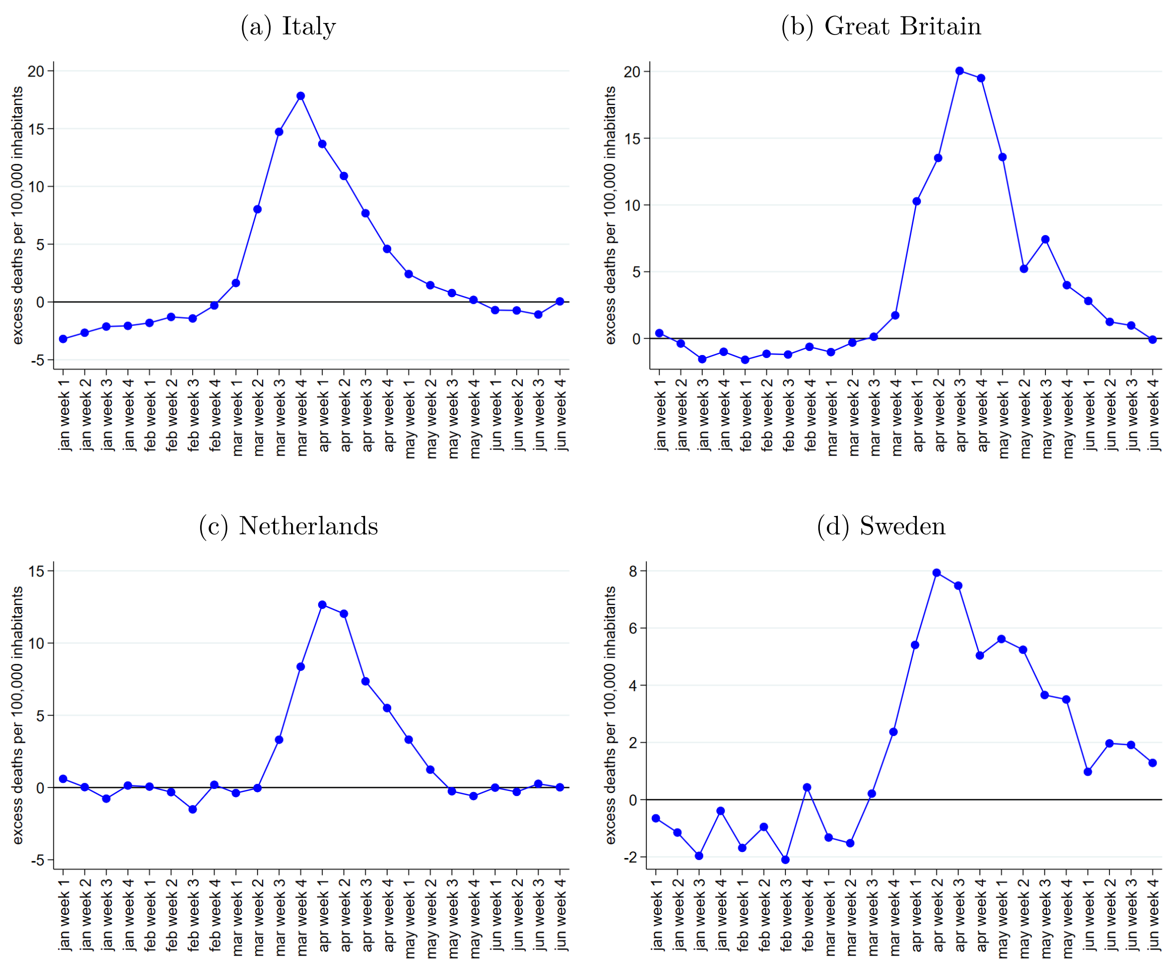
Notes: This table displays the timeline of the policy measures implemented in all countries.

Figure A.1: Number of cases per 100,000 inhabitants at the national level over time



Notes: The graph shows the development of the pandemic for each country over time expressed as the number of infections per 100,000 inhabitants. The dashed line marks the end of our baseline sample.

Figure A.2: Number of excess deaths at the national level over time



Notes: The graph shows the number of excess deaths in Italy, the Netherlands and Great Britain between January and June 2020 per 100,000 inhabitants. Excess mortality as the difference in the number of deaths in a given period in 2020 and the average number of deaths in the same period from 2015 to 2019. For the Netherlands, our reference period includes only 2019, since earlier data is not available.

B Simple SIR model

In order to illustrate and validate our empirical strategy, we use data from a simulated Susceptible-Infected-Recovered (SIR) model in discrete time (Kermack et al. 1927). The model consists of the following three equations:

$$I_{t+1} = I_t + \beta_t S_t \frac{I_t}{N}$$

$$S_{t+1} = S_t - \beta_t S_t \frac{I_t}{N}$$

$$R_{t+1} = R_t + \gamma I_t \; .$$

The number of infected individuals I_{t+1} is determined by the contact rate β_t, multiplied with the stock of susceptible individuals S_t and already infected individuals I_t and divided by the total population $N = S+I+R$. The change in the number of susceptible individuals is the mirror image of the change in infected individuals. Moreover, a fraction γ of the infected individuals recovers each day.

In order to model the relevant dynamics in the context of our study, we distinguish three periods p. The first period lasts from the outbreak of the virus to the time when agents become aware of the disease (phase 1), the second lasts from the point of awareness to the beginning of a lockdown (phase 2), and the third is the post-lockdown period (phase 3). We set $N = 100,000$ and draw the initial number of infected I_0 from a uniform distribution between 1 and 10.

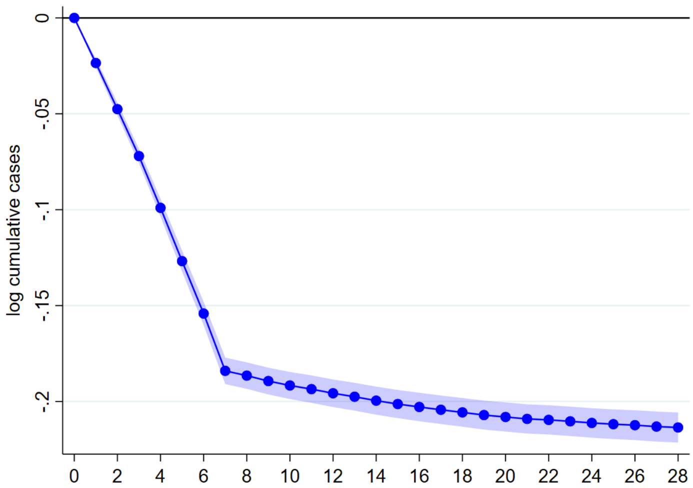
The contact rate beta is specified as $\beta_{ip} = \beta_0 \cdot exp(\alpha_p \cdot sc_i + \epsilon_{it})$ for $p \in \{1,2\}$, where sc_i is social capital in area i, drawn from a normal distribution with mean zero and standard deviation 0.5, and $\epsilon_{it} \sim N(0, 0.2)$ is a random error term drawn for each area i and day t. We assume that during the first 7 days (phase 1), agents are unaware of the virus. In the baseline simulation, we set $\alpha_1 = 0$, meaning that the contact rate is initially the same everywhere. For γ and β_0, we choose the values 0.1 and 0.25, implying an initial basic reproduction number R_0 of 2.5. If α_1 was positive, a case which we will explore below, the spread of the virus would initially be greater in high- than in low-social-capital areas. In phase 2, agents become aware of the risks of the disease and adapt their behavior accordingly. We set $\alpha_2 = -0.3$, which implies that once agents become aware of the virus, those living in high-social-capital areas reduce their contacts by more compared to those in low-social-capital areas. Finally, in phase $p = 3$, starting on day 14, there is a lockdown, where all areas have the same contact rate $\beta_{i3} = \beta_0 \cdot exp(\alpha_3 + \epsilon_{it})$. We set $\alpha_3 = -1$, implying that the reproduction number will fall below 1 after the lockdown.[23]

We simulate the model for 1,000 areas and $T = 35$ days. Based on the resulting data, we then estimate our reduced-form model described in equation (1). Similar to our real-world, reduced-form evidence, we assume that data on cases are only observable to researchers from day 7 on, such that day 8 after the outbreak is the first date of our estimation sample. As discussed above, in our real-world data this limitation is driven by the fact that a micro-area has to have a positive number of cases to be included in the sample. Choosing a too early starting date means there are only few areas, resulting in imprecise estimates. The choice of the late sample start in the simulation will help us to validate whether this is an issue in identifying the effect of social capital.

The results are presented in Figure B.1. The pattern is similar to the one we find in our empirical regressions: we first observe a steep decline in the growth of cases in high- compared to low-social-capital areas. After the lockdown, both types of areas embark on

[23] Of course, it would be possible to assume that even during a lockdown high-social-capital areas have different contact rates than low-social-capital areas. Given that the purpose of the model is merely to demonstrate that our empirical model is able to identify the pandemic dynamics, we chose the simpler assumption of equal contact rates.

Figure B.1: Baseline results estimated on simulated data

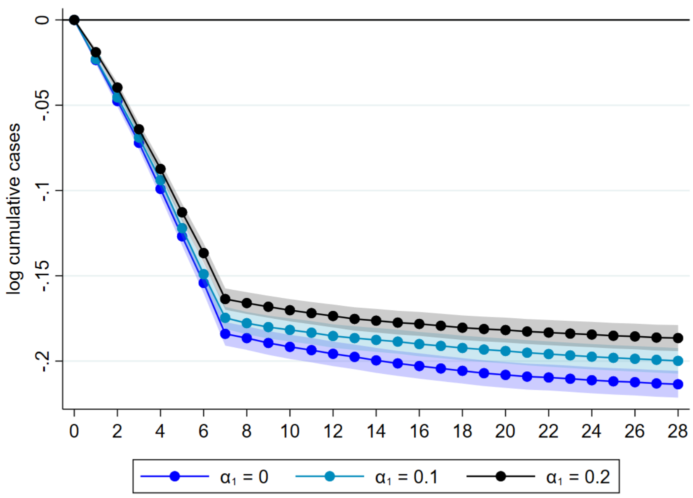


Notes: The graph shows the results from estimating our baseline model (1) on data simulated from the SIR model.

a similar growth trajectory.[24]

We conduct two simulation exercises that assess the robustness of our estimation strategy with respect to pitfalls in the data structure of cases in the early phase of a pandemic caused by a new virus. First, we assess the bias that arises when high-social-capital areas initially have a higher number of cases. In particular, we explore the effect of allowing different values for α_1, letting it vary from 0 to 0.2. This implies that high-social-capital

Figure B.2: Effect of differential initial growth

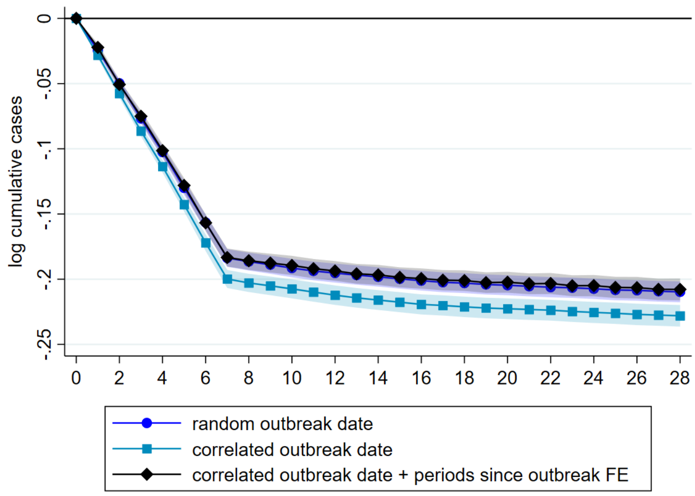


Notes: The graph shows the results from estimating our baseline model (1) on data simulated from the SIR model, generated based on different values for the contact rate α_1.

[24]Note that in the model, unlike in the data, there is no lag due to incubation time, testing and reporting.

areas have a higher number of cases when the sample starts, as we observe in the real-world data. Figure B.2 shows that increasing α_1 actually *decreases* the estimated effect of social capital. This is explained by the higher initial level of infected individuals in high-social-capital areas: because the chance of meeting an infected person is greater in high-social-capital areas, initially every contact becomes riskier and the behavioral response in principle has to be greater to achieve the same effect. This implies that under a scenario with positive α_1 our empirical specification can be interpreted as a lower bound for the effect of the behavioral change.

Figure B.3: Effect of periods-since-outbreak fixed effects



Notes: The graph shows the results from estimating our baseline model (1) on data simulated from the SIR model. The dotted blue line shows the results for the case of a random outbreak date. The squared light blue line shows results for the case when the outbreak date is correlated with social capital. The black line with diamonds shows results for the correlated case with period-since-outbreak fixed effects.

In the second simulation exercise, we relax the assumption that the pandemic starts on the same day in each area. Here, the concern is that high- and low-social capital areas are at different points of the infection curve, such that our estimates do not pick up the effect of social capital, but these systematically different dynamics. We test whether period-since-outbreak fixed effects are able to account for the resulting bias. As a benchmark, we draw a random start date for each area from a uniform distribution between days 0 and 6. Next, we impose a negative correlation between the start date and social capital, such that high-social-capital areas are hit earlier by the virus. We set the correlation to a relatively high value of -0.5 for illustrative purposes.[25] We estimate both our baseline model and a model with period-since-outbreak fixed effects on the simulated data. Figure B.3 illustrates the effect of using the period-since-outbreak fixed effects. The dotted blue line shows the results for the case when the outbreak date is random. The squared light

[25] In the actual data, when pooling across all countries, we estimate a more modest correlation of -0.09 between social capital and the start date within regions across countries.

blue line shows results for the same regression when the outbreak date is correlated with social capital. We see that in this case, the point estimates become slightly larger in absolute value, meaning that we would overstate the social capital effect. However, once we include period-since-outbreak fixed effects, we can recover the original estimates, as shown by the black line with diamonds.[26]

C Additional Results

Table C.1: Effect of social capital on the spread of Covid-19 cases with controls

	(1)		(2)		(3)		(4)	
Panel A – Italy								
turnout x 30jun2020	-0.412**	(0.178)	-0.332**	(0.163)	-0.340**	(0.163)	-0.337*	(0.199)
province FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	4.947		4.947		4.955		4.955	
observations	12,175		12,175		12,085		12,085	
Panel B – Great Britain								
turnout x 30jun2020	-0.278***	(0.052)	-0.270***	(0.050)	-0.272***	(0.050)	-0.177***	(0.065)
lower tier local authority FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	4.967		4.967		4.968		4.968	
observations	40,065		40,065		39,823		39,823	
Panel C – Germany								
turnout x 30jun2020	-0.152***	(0.053)	-0.084	(0.055)	-0.097*	(0.057)	-0.108*	(0.061)
county FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	4.724		4.724		4.724		4.724	
observations	43,393		43,392		43,268		43,268	
Panel D – Switzerland								
turnout x 30jun2020	-0.280***	(0.069)	-0.279***	(0.069)	-0.274***	(0.070)	-0.196**	(0.076)
municipality FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	5.384		5.384		5.384		5.384	
observations	185,195		185,195		185,195		185,195	
Panel E – The Netherlands								
turnout x 30jun2020	-0.325***	(0.090)	-0.318***	(0.088)	-0.322***	(0.088)	-0.270**	(0.114)
municipality FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	4.891		4.891		4.895		4.895	
observations	37,965		37,965		37,849		37,849	

continued

[26]Note that this implies that we do not need to assume that we observe the true start date in the data. It is sufficient to assume that the lag between the true and observed start date is not systematically related to social capital.

Table C.1 continued

	(1)		(2)		(3)		(4)	
Panel F – Austria								
turnout x 28jun2020	-0.222***	(0.074)	-0.222***	(0.074)	-0.223***	(0.074)	-0.200***	(0.073)
municipality FE	yes		yes		yes		yes	
NUTS1 x week FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x week FE	no		no		yes		yes	
controls x week FE	no		no		no		yes	
mean	5.017		5.017		5.017		5.017	
observations	21,220		21,220		21,220		21,220	
Panel G – Sweden								
turnout x 28jun2020	-0.232**	(0.097)	-0.243**	(0.108)	-0.256**	(0.109)	-0.442**	(0.196)
municipality FE	yes		yes		yes		yes	
NUTS1 x week FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x week FE	no		no		yes		yes	
controls x week FE	no		no		no		yes	
mean	4.926		4.924		4.925		4.925	
observations	3,864		3,861		3,843		3,843	

Notes: This table presents the regression results in equation (2). For the sake of brevity, we omit all coefficients, but the last one. All coefficients are available upon request. Standard errors clustered at the micro-area level in parenthesis. Column (2) adds weeks-since-outbreak FE and column (3) adds weeks-since-outbreak x date FE. Column (4) additionally adds controls interacted with date FE. Statistical significance denoted as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Effect of social capital on the spread of Covid-19 cases with controls: second wave

	(1)		(2)		(3)		(4)	
Panel A – Italy								
turnout x 31dec2020	-0.756***	(0.229)	-0.661***	(0.211)	-0.660***	(0.213)	-0.578**	(0.238)
province FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	5.826		5.826		5.833		5.833	
observations	31,862		31,862		31,615		31,615	
Panel B – Great Britain								
turnout x 31dec2020	-0.349***	(0.052)	-0.341***	(0.050)	-0.344***	(0.050)	-0.232***	(0.067)
lower tier local authority FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	6.034		6.034		6.034		6.034	
observations	107,957		107,956		107,297		107,297	
Panel C – Germany								
turnout x 31dec2020	-0.268***	(0.053)	-0.214***	(0.054)	-0.230***	(0.057)	-0.207***	(0.061)
county FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	5.524		5.524		5.520		5.520	
observations	116,813		116,813		116,102		116,102	
Panel D – Switzerland								
turnout x 31dec2020	-0.349***	(0.070)	-0.380***	(0.070)	-0.368***	(0.070)	-0.240***	(0.080)
municipality FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	6.253		6.253		6.253		6.253	
observations	554,601		554,601		554,123		554,123	

continued

Table C.2 continued

	(1)		(2)		(3)		(4)	
Panel E – The Netherlands								
turnout x 31dec2020	-0.380***	(0.094)	-0.387***	(0.091)	-0.374***	(0.091)	-0.325***	(0.115)
municipality FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	5.972		5.972		5.975		5.975	
observations	102,998		102,997		102,544		102,544	
Panel F – Austria								
turnout x 27dec2020	-0.231***	(0.065)	-0.249***	(0.065)	-0.249***	(0.065)	-0.191***	(0.065)
municipality FE	yes		yes		yes		yes	
NUTS1 x week FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x week FE	no		no		yes		yes	
controls x week FE	no		no		no		yes	
mean	5.952		5.952		5.952		5.952	
observations	72,101		72,101		72,095		72,095	
Panel G – Sweden								
turnout x 28dec2020	-0.467***	(0.169)	-0.478***	(0.185)	-0.492***	(0.182)	-0.869**	(0.343)
municipality FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x week FE	no		no		yes		yes	
controls x week FE	no		no		no		yes	
mean	5.880		5.880		5.890		5.890	
observations	11,739		11,736		11,583		11,583	

Notes: This table presents the regression results in equation (1) for the second wave. For the sake of brevity, we omit all coefficients, but the last one. All coefficients are available upon request. Standard errors clustered at the micro-area level in parenthesis. Column (2) adds weeks-since-outbreak FE and column (3) adds weeks-since-outbreak x date FE. Column (4) additionally adds controls interacted with date FE. Statistical significance denoted as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Effect of social capital on the spread of Covid-19 cases: alternative measures

	(1)		(2)		(3)		(4)	
Panel A – Italy								
blood donations per capita x 30jun2020	-0.197**	(0.090)	-0.211**	(0.086)	-0.213**	(0.087)	-0.234**	(0.104)
province FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	4.929		4.929		4.937		4.937	
observations	11,719		11,719		11,629		11,629	
Panel B – Netherlands								
organ donors per capita x 30jun2020	-0.285***	(0.084)	-0.288***	(0.082)	-0.293***	(0.082)	-0.163**	(0.074)
municipality FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	4.891		4.891		4.895		4.895	
observations	37,965		37,965		37,849		37,849	
Panel C – Great Britain								
blood donors per capita x 30jun2020	-0.249***	(0.076)	-0.279***	(0.071)	-0.281***	(0.072)	-0.222**	(0.089)
lower tier local authority FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	4.967		4.967		4.968		4.968	
observations	40,065		40,065		39,823		39,823	
Panel D – Germany								
associations per 1k inhabitants x 30jun2020	-0.115**	(0.049)	-0.125***	(0.046)	-0.124***	(0.047)	-0.103**	(0.049)

continued

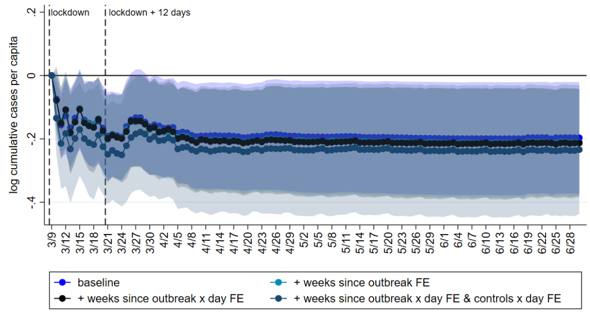
Table C.3 continued

	(1)		(2)		(3)		(4)	
county FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		yes		no		no	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	4.724		4.724		4.724		4.724	
observations	43,393		43,392		43,268		43,268	
Panel E − Italy								
literacy rate in 1821 x 30jun2020	-0.370**	(0.184)	-0.334*	(0.168)	-0.336*	(0.169)	-0.361	(0.229)
province FE	yes		yes		yes		yes	
NUTS1 x day FE	yes		yes		yes		yes	
weeks-since-outbreak FE	no		no		yes		yes	
weeks-since-outbreak x day FE	no		no		no		yes	
controls x day FE	no		no		no		yes	
mean	4.955		4.955		4.957		4.957	
observations	7,927		7,927		7,912		7,912	

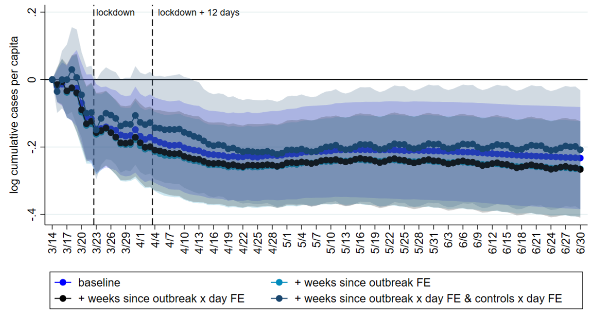
Notes: This table presents the regression results from our baseline model in equation (1) using blood donations per capita (Italy and Great Britain), registered organ donors per capita (Netherlands), associations per capita (Germany) and literacy rates in 1821 (Italy). For the sake of brevity, we omit all coefficients, but the last one. All coefficients are available upon request. Standard errors clustered at the micro-area level in parenthesis. Column (2) adds weeks-since-outbreak FE and column (3) adds weeks-since-outbreak x day FE. Column (4) additionally adds controls interacted with day FE. Statistical significance denoted as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure C.1: Alternative social capital measures with additional fixed effects and controls

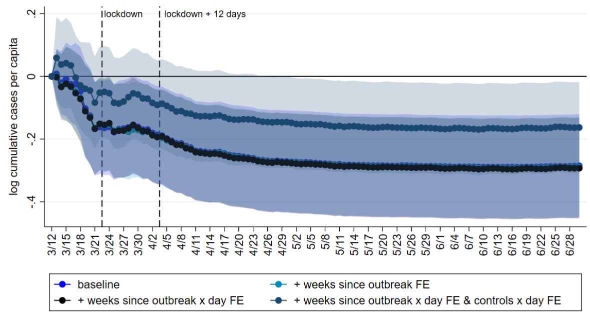
(a) Blood donations per capita, Italy



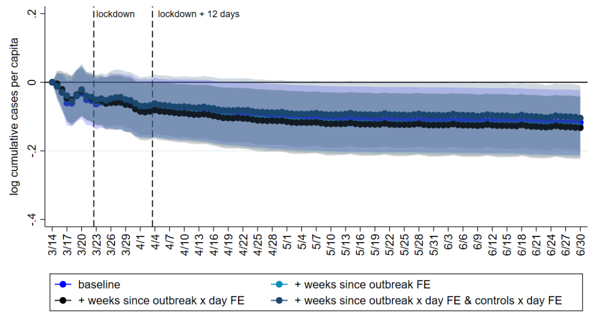
(b) Blood donations per capita, Great Britain



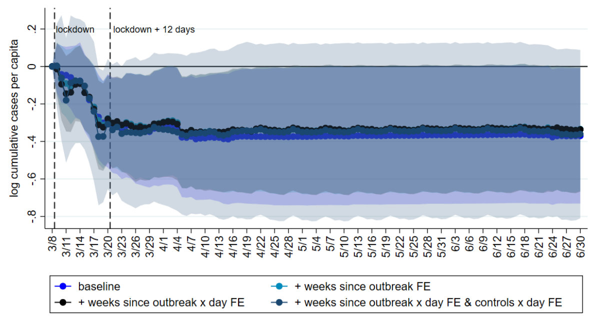
(c) Organ donors per capita, Netherlands



(d) Associations per capita, Germany



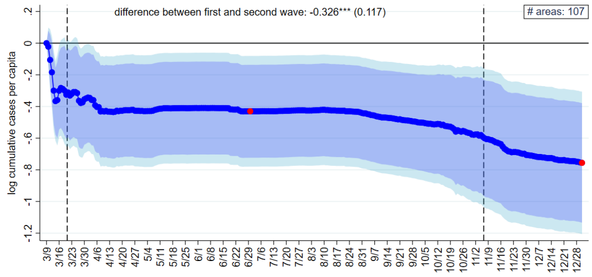
(e) Literacy rates in 1821, Italy



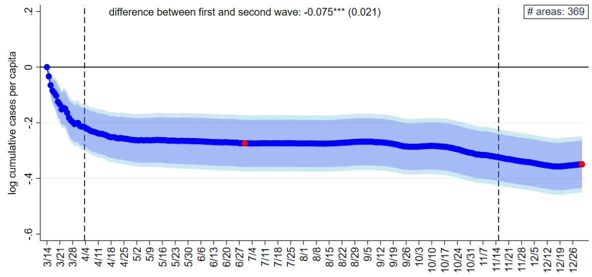
Notes: The figure shows the estimation results of the impact of social capital on the evolution of Covid-19 infections. They are based on the estimation model outlined in equation (2) and the outcome variable is the log cumulative number of Covid-19 infections per 100,000 inhabitants. The light-blue line includes weeks-since-outbreak fixed effects; the black line includes weeks-since-outbreak x day fixed effects. The grey line additionally includes a set of controls interacted with day fixed affects. In panels (a) and (b) we use blood donations per capita as our proxy for social capital, in panel (c) we use the number of registered organ donors per capita as a proxy, in panel (d) we use associations per capita, in panel (e) literacy rates in 1821 (see Table C.3 for point estimates).

Figure C.2: Effect of social capital on the spread of Covid-19 cases: second wave

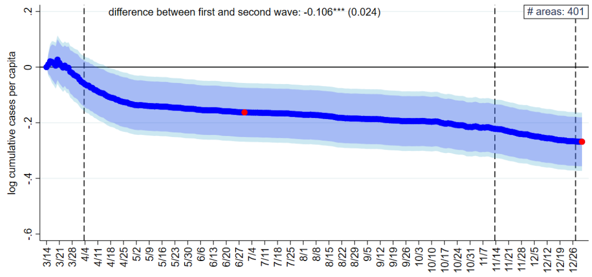
(a) Italy



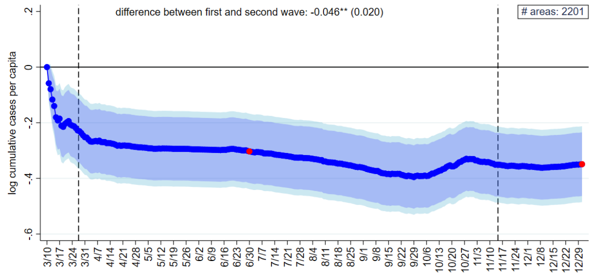
(b) Great Britain



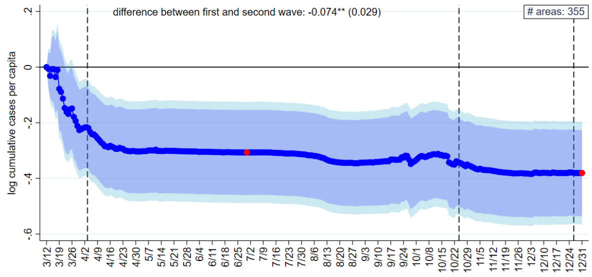
(c) Germany



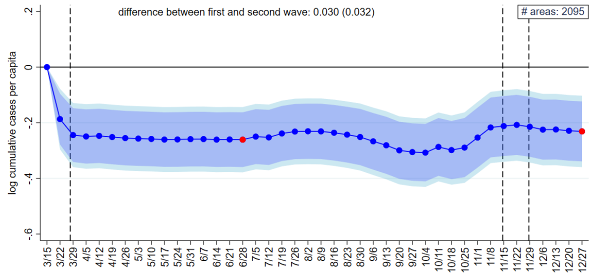
(d) Switzerland



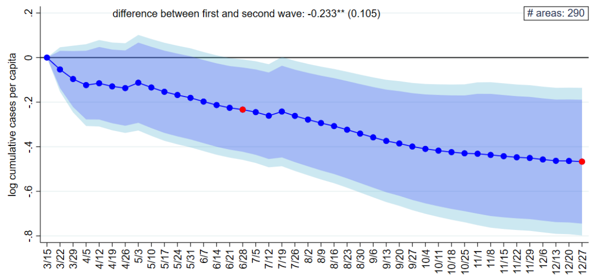
(e) Netherlands



(f) Austria



(g) Sweden



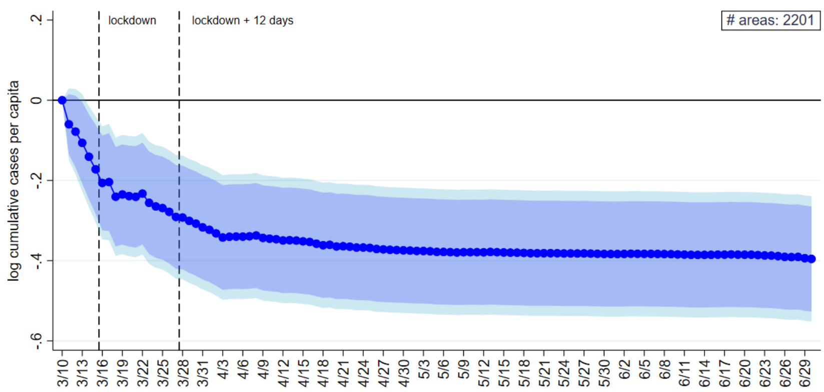
Notes: The figure presents the differential evolution of the relationship between cumulative Covid-19 infections per 100,000 inhabitants and social capital across time. The estimates are based on the model outlined in equation (1) (see Table C.2 for the point estimates). The difference at the top of each panel refers to a test of the difference between the last point estimate and the one at the end of our baseline sample, marked by the red dots. The dashed lines mark the date of the national lockdown plus 12 days to account for incubation plus confirmation time. Since there was no official lockdown in Sweden, no dashed lines are displayed in panel (g). The dark (light) blue area corresponds to the 90% (95%) confidence interval.

Table C.4: Selection on unobservables: Oster (2019)

	(1) uncontrolled coefficient	(2) controlled coefficient	(3) bounded coefficient
Italy	-0.340	-0.337	-0.336
	[0.008]	[0.057]	
Great Britain	-0.272	-0.177	-0.128
	[0.028]	[0.068]	
Germany	-0.097	-0.108	-0.114
	[0.023]	[0.052]	
Switzerland	-0.274	-0.196	-0.166
	[0.014]	[0.070]	
Austria	-0.223	-0.200	-0.191
	[0.015]	[0.052]	
Netherlands	-0.322	-0.270	-0.237
	[0.056]	[0.108]	
Sweden	-0.257	-0.442	-0.511
	[0.010]	[0.054]	

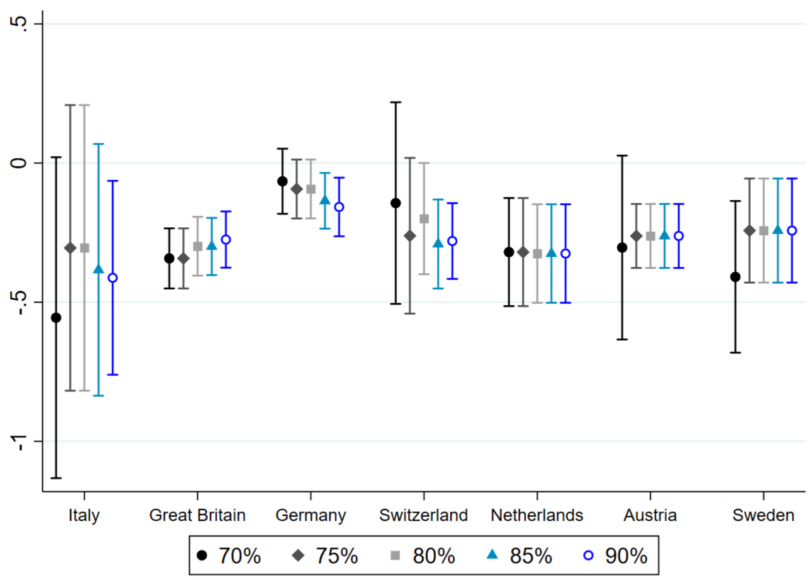
Notes: This table reports the turnout coefficients for each country at the final day of our sample. Column 1 presents our baseline results from equation (1) including the weeks since outbreak x time fixed effects. Column 2 reports the same coefficients if we include our set of controls interacted with day fixed effects. Column 3 reports the bounds on the coefficients based on the adjustment strategy by Oster (2019). The R^2 of each model is presented in square brackets. We obtain these bounds by choosing R_{max} equal to 1.3 times the R^2 of the controlled model and setting δ equal to 1.

Figure C.3: Effect of social capital on Covid-19 cases: Swiss municipalities with NUTS-3 fixed effects



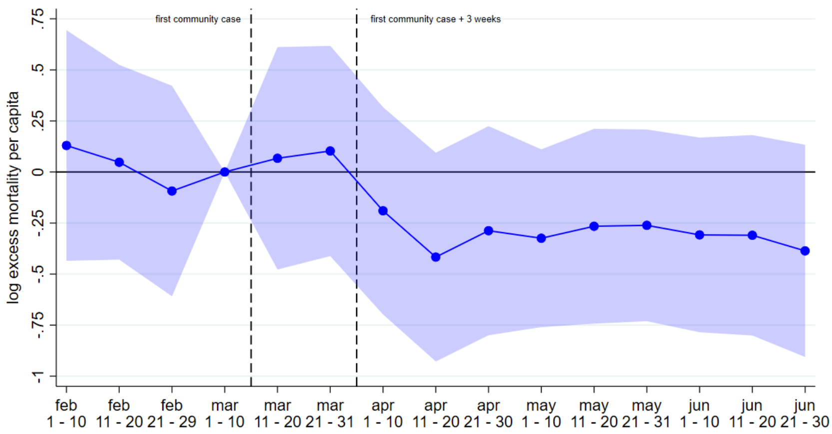
Notes: The figure presents the differential evolution of the relationship between cumulative Covid-19 cases per 100,000 inhabitants and social capital across time. The estimates are based on the model outlined in equation (1) including controls and NUTS-3 x day FE instead of NUTS-1 x day FE. The first dashed line marks the date of the national lockdown, the second dashed line the date of the national lockdown plus 12 days to account for incubation plus confirmation time. The dark (light) blue area corresponds to the 90% (95%) confidence interval.

Figure C.4: Effect of social capital on Covid-19 cases: by threshold



Notes: The figure plots the estimate on June 30 from equation (1) and the corresponding 95% confidence interval, varying the threshold criterion used to choose the start date of the sample for each country. The sample starts when more than a certain percentage from 70% to 90% of NUTS-3 regions in a country have experienced at least one case. Since we have weekly data for Austria and Sweden, the sample start always falls in the same week. Therefore, we shift the sample start backwards by one week for the 70% criterion for those countries.

Figure C.5: Effect of social capital on excess deaths: Swedish municipalities in 10-day blocks



Notes: The figure presents the differential evolution of the relationship between cumulative excess deaths per 100,000 inhabitants and social capital across time. The estimates are based on the model outlined in equation (3). The shaded areas correspond to the 95% confidence interval.

Table C.5: Effect of social capital on excess deaths

	(1)		(2)	
Panel A – Italy				
turnout x 01feb2020	-0.025	(0.029)	-0.026	(0.030)
turnout x 02feb2020	-0.025	(0.029)	-0.023	(0.030)
turnout x 03feb2020	-0.019	(0.028)	-0.017	(0.028)
turnout x 04feb2020	-0.025	(0.028)	-0.022	(0.028)
turnout x 05feb2020	-0.004	(0.027)	-0.003	(0.027)
turnout x 06feb2020	-0.003	(0.027)	0.002	(0.028)
turnout x 07feb2020	-0.000	(0.027)	0.004	(0.027)
turnout x 08feb2020	0.021	(0.026)	0.022	(0.026)
turnout x 09feb2020	0.008	(0.026)	0.012	(0.026)
turnout x 10feb2020	0.005	(0.026)	0.007	(0.026)
turnout x 11feb2020	-0.000	(0.024)	0.003	(0.025)
turnout x 12feb2020	-0.006	(0.024)	-0.003	(0.025)
turnout x 13feb2020	-0.018	(0.024)	-0.019	(0.024)
turnout x 14feb2020	-0.028	(0.022)	-0.027	(0.023)
turnout x 15feb2020	-0.024	(0.021)	-0.023	(0.021)
turnout x 16feb2020	-0.017	(0.022)	-0.019	(0.022)
turnout x 17feb2020	-0.029	(0.019)	-0.030	(0.020)
turnout x 18feb2020	-0.020	(0.017)	-0.019	(0.017)
turnout x 19feb2020	-0.027*	(0.014)	-0.027*	(0.014)
turnout x 21feb2020	0.013	(0.013)	0.012	(0.013)
turnout x 22feb2020	0.006	(0.017)	0.006	(0.017)
turnout x 23feb2020	-0.017	(0.018)	-0.016	(0.018)
turnout x 24feb2020	-0.008	(0.019)	-0.008	(0.020)
turnout x 25feb2020	-0.001	(0.021)	-0.004	(0.021)
turnout x 26feb2020	0.006	(0.022)	0.003	(0.022)
turnout x 27feb2020	0.001	(0.023)	-0.002	(0.024)
turnout x 28feb2020	-0.019	(0.024)	-0.020	(0.024)
turnout x 29feb2020	-0.005	(0.024)	-0.004	(0.025)
turnout x 01mar2020	-0.006	(0.025)	-0.006	(0.025)
turnout x 02mar2020	-0.019	(0.026)	-0.021	(0.026)
turnout x 03mar2020	0.005	(0.025)	0.001	(0.026)
turnout x 04mar2020	0.018	(0.025)	0.017	(0.026)
turnout x 05mar2020	0.011	(0.026)	0.010	(0.026)
turnout x 06mar2020	0.025	(0.026)	0.029	(0.027)
turnout x 07mar2020	0.024	(0.026)	0.022	(0.026)
turnout x 08mar2020	0.009	(0.026)	0.006	(0.026)
turnout x 09mar2020	0.027	(0.026)	0.025	(0.027)
turnout x 10mar2020	0.030	(0.027)	0.024	(0.027)
turnout x 11mar2020	0.015	(0.027)	0.010	(0.027)
turnout x 12mar2020	0.020	(0.027)	0.015	(0.028)

continued

Table C.5 continued

	(1)		(2)	
turnout x 13mar2020	0.004	(0.028)	-0.003	(0.029)
turnout x 14mar2020	0.001	(0.028)	-0.009	(0.028)
turnout x 15mar2020	0.003	(0.029)	-0.005	(0.029)
turnout x 16mar2020	-0.003	(0.028)	-0.011	(0.029)
turnout x 17mar2020	0.016	(0.029)	0.010	(0.029)
turnout x 18mar2020	0.006	(0.029)	0.000	(0.029)
turnout x 19mar2020	-0.002	(0.029)	-0.010	(0.029)
turnout x 20mar2020	0.004	(0.029)	-0.005	(0.029)
turnout x 21mar2020	-0.023	(0.030)	-0.035	(0.030)
turnout x 22mar2020	-0.019	(0.029)	-0.034	(0.029)
turnout x 23mar2020	-0.037	(0.029)	-0.051*	(0.029)
turnout x 24mar2020	-0.038	(0.029)	-0.054*	(0.029)
turnout x 25mar2020	-0.041	(0.030)	-0.057*	(0.030)
turnout x 26mar2020	-0.039	(0.030)	-0.056*	(0.030)
turnout x 27mar2020	-0.025	(0.030)	-0.045	(0.030)
turnout x 28mar2020	-0.047	(0.030)	-0.063**	(0.030)
turnout x 29mar2020	-0.049*	(0.030)	-0.069**	(0.030)
turnout x 30mar2020	-0.053*	(0.031)	-0.075**	(0.031)
turnout x 31mar2020	-0.049	(0.030)	-0.073**	(0.030)
turnout x 01apr2020	-0.052*	(0.030)	-0.075**	(0.030)
turnout x 02apr2020	-0.046	(0.031)	-0.070**	(0.031)
turnout x 03apr2020	-0.049	(0.030)	-0.070**	(0.031)
turnout x 04apr2020	-0.044	(0.031)	-0.068**	(0.031)
turnout x 05apr2020	-0.051*	(0.031)	-0.077**	(0.031)
turnout x 06apr2020	-0.054*	(0.031)	-0.081***	(0.031)
turnout x 07apr2020	-0.054*	(0.031)	-0.080***	(0.031)
turnout x 08apr2020	-0.040	(0.031)	-0.067**	(0.031)
turnout x 09apr2020	-0.043	(0.031)	-0.071**	(0.031)
turnout x 10apr2020	-0.047	(0.031)	-0.073**	(0.032)
turnout x 11apr2020	-0.050	(0.031)	-0.076**	(0.032)
turnout x 12apr2020	-0.058*	(0.031)	-0.085***	(0.032)
turnout x 13apr2020	-0.053*	(0.031)	-0.079**	(0.031)
turnout x 14apr2020	-0.059*	(0.031)	-0.083***	(0.031)
turnout x 15apr2020	-0.049	(0.031)	-0.075**	(0.031)
turnout x 16apr2020	-0.067**	(0.031)	-0.092***	(0.031)
turnout x 17apr2020	-0.064**	(0.031)	-0.089***	(0.031)
turnout x 18apr2020	-0.053*	(0.031)	-0.077**	(0.031)
turnout x 19apr2020	-0.067**	(0.031)	-0.089***	(0.032)
turnout x 20apr2020	-0.059*	(0.031)	-0.082***	(0.032)
turnout x 21apr2020	-0.056*	(0.031)	-0.080**	(0.031)
turnout x 22apr2020	-0.052*	(0.031)	-0.077**	(0.031)
turnout x 23apr2020	-0.050	(0.031)	-0.074**	(0.031)
turnout x 24apr2020	-0.046	(0.031)	-0.070**	(0.031)
turnout x 25apr2020	-0.047	(0.031)	-0.071**	(0.031)
turnout x 26apr2020	-0.049	(0.031)	-0.073**	(0.032)
turnout x 27apr2020	-0.059*	(0.032)	-0.084***	(0.032)
turnout x 28apr2020	-0.063**	(0.032)	-0.087***	(0.032)
turnout x 29apr2020	-0.069**	(0.032)	-0.094***	(0.032)
turnout x 30apr2020	-0.064**	(0.032)	-0.089***	(0.032)
turnout x 01may2020	-0.068**	(0.032)	-0.095***	(0.032)
turnout x 02may2020	-0.077**	(0.032)	-0.105***	(0.032)
turnout x 03may2020	-0.077**	(0.032)	-0.103***	(0.032)
turnout x 04may2020	-0.077**	(0.032)	-0.104***	(0.032)
turnout x 05may2020	-0.080**	(0.032)	-0.105***	(0.032)
turnout x 06may2020	-0.084***	(0.032)	-0.110***	(0.033)
turnout x 07may2020	-0.086***	(0.032)	-0.110***	(0.032)
turnout x 08may2020	-0.080**	(0.033)	-0.106***	(0.033)
turnout x 09may2020	-0.077**	(0.032)	-0.104***	(0.032)
turnout x 10may2020	-0.075**	(0.033)	-0.102***	(0.033)
turnout x 11may2020	-0.083**	(0.033)	-0.109***	(0.033)
turnout x 12may2020	-0.077**	(0.033)	-0.101***	(0.033)
turnout x 13may2020	-0.071**	(0.033)	-0.097***	(0.033)
turnout x 14may2020	-0.077**	(0.033)	-0.104***	(0.033)
turnout x 15may2020	-0.080**	(0.032)	-0.106***	(0.032)
turnout x 16may2020	-0.080**	(0.032)	-0.105***	(0.032)
turnout x 17may2020	-0.087***	(0.032)	-0.111***	(0.032)
turnout x 18may2020	-0.078**	(0.032)	-0.102***	(0.033)
turnout x 19may2020	-0.078**	(0.032)	-0.102***	(0.032)
turnout x 20may2020	-0.082**	(0.032)	-0.106***	(0.032)
turnout x 21may2020	-0.071**	(0.032)	-0.096***	(0.032)
turnout x 22may2020	-0.065**	(0.032)	-0.091***	(0.033)
turnout x 23may2020	-0.065**	(0.032)	-0.091***	(0.032)
turnout x 24may2020	-0.063**	(0.032)	-0.090***	(0.032)
turnout x 25may2020	-0.063*	(0.033)	-0.089***	(0.033)
turnout x 26may2020	-0.067**	(0.032)	-0.092***	(0.032)
turnout x 27may2020	-0.070**	(0.032)	-0.096***	(0.032)
turnout x 28may2020	-0.076**	(0.032)	-0.101***	(0.032)
turnout x 29may2020	-0.085***	(0.032)	-0.111***	(0.033)

continued

Table C.5 continued

	(1)		(2)	
turnout x 30may2020	-0.090***	(0.033)	-0.117***	(0.033)
turnout x 31may2020	-0.084**	(0.033)	-0.111***	(0.033)
turnout x 01jun2020	-0.089***	(0.033)	-0.115***	(0.033)
turnout x 02jun2020	-0.090***	(0.033)	-0.119***	(0.033)
turnout x 03jun2020	-0.088***	(0.033)	-0.118***	(0.033)
turnout x 04jun2020	-0.091***	(0.033)	-0.120***	(0.033)
turnout x 05jun2020	-0.091***	(0.033)	-0.119***	(0.033)
turnout x 06jun2020	-0.084**	(0.033)	-0.113***	(0.033)
turnout x 07jun2020	-0.082**	(0.033)	-0.111***	(0.033)
turnout x 08jun2020	-0.077**	(0.033)	-0.106***	(0.034)
turnout x 09jun2020	-0.081**	(0.033)	-0.110***	(0.034)
turnout x 10jun2020	-0.082**	(0.033)	-0.111***	(0.033)
turnout x 11jun2020	-0.079**	(0.033)	-0.108***	(0.033)
turnout x 12jun2020	-0.080**	(0.033)	-0.109***	(0.033)
turnout x 13jun2020	-0.081**	(0.033)	-0.109***	(0.033)
turnout x 14jun2020	-0.080**	(0.033)	-0.110***	(0.034)
turnout x 15jun2020	-0.077**	(0.033)	-0.107***	(0.034)
turnout x 16jun2020	-0.061*	(0.033)	-0.088***	(0.033)
turnout x 17jun2020	-0.063*	(0.033)	-0.090***	(0.033)
turnout x 18jun2020	-0.071**	(0.033)	-0.097***	(0.033)
turnout x 19jun2020	-0.078**	(0.033)	-0.105***	(0.033)
turnout x 20jun2020	-0.078**	(0.033)	-0.105***	(0.033)
turnout x 21jun2020	-0.071**	(0.033)	-0.098***	(0.033)
turnout x 22jun2020	-0.075**	(0.033)	-0.106***	(0.033)
turnout x 23jun2020	-0.066**	(0.033)	-0.097***	(0.033)
turnout x 24jun2020	-0.058*	(0.033)	-0.090***	(0.034)
turnout x 25jun2020	-0.048	(0.034)	-0.079**	(0.034)
turnout x 26jun2020	-0.057*	(0.034)	-0.088**	(0.034)
turnout x 27jun2020	-0.071**	(0.034)	-0.099***	(0.034)
turnout x 28jun2020	-0.070**	(0.034)	-0.099***	(0.034)
turnout x 29jun2020	-0.073**	(0.034)	-0.105***	(0.034)
turnout x 30jun2020	-0.063*	(0.034)	-0.095***	(0.034)
municipality FE	yes		yes	
NUTS3 x day FE	yes		yes	
controls x day FE	no		yes	
mean	4.653		4.653	
observations	592,128		592,128	
Panel B − Netherlands				
turnout x feb week 1	-0.053	(0.080)	-0.129	(0.091)
turnout x feb week 2	-0.042	(0.072)	-0.067	(0.077)
turnout x feb week 4	-0.033	(0.066)	-0.118	(0.078)
turnout x mar week 1	-0.028	(0.080)	-0.064	(0.093)
turnout x mar week 2	-0.060	(0.096)	-0.185*	(0.108)
turnout x mar week 3	-0.059	(0.086)	-0.092	(0.099)
turnout x mar week 4	-0.071	(0.092)	-0.104	(0.100)
turnout x apr week 1	-0.157*	(0.092)	-0.187*	(0.102)
turnout x apr week 2	-0.155*	(0.090)	-0.186*	(0.101)
turnout x apr week 3	-0.174*	(0.092)	-0.205*	(0.105)
turnout x apr week 4	-0.177**	(0.086)	-0.187**	(0.094)
turnout x may week 1	-0.215**	(0.087)	-0.190**	(0.096)
turnout x may week 2	-0.207**	(0.085)	-0.178*	(0.094)
turnout x may week 3	-0.249***	(0.088)	-0.209**	(0.095)
turnout x may week 4	-0.279***	(0.089)	-0.234**	(0.102)
turnout x jun week 1	-0.229***	(0.086)	-0.210**	(0.097)
turnout x jun week 2	-0.202**	(0.086)	-0.172*	(0.099)
turnout x jun week 3	-0.164*	(0.090)	-0.210**	(0.099)
turnout x jun week 4	-0.227**	(0.089)	-0.173*	(0.098)
controls x week FE	no		yes	
municipality FE	yes		yes	
NUTS3 x week FE	yes		yes	
mean	3.756		3.756	
observations	4,969		4,969	
Panel C − Great Britain				
turnout x feb week 1	-0.150	(0.136)	-0.362*	(0.213)
turnout x feb week 2	-0.190	(0.167)	-0.097	(0.234)
turnout x feb week 3	-0.354**	(0.139)	-0.249	(0.219)
turnout x mar week 1	0.025	(0.163)	-0.252	(0.261)
turnout x mar week 2	0.014	(0.137)	-0.198	(0.196)
turnout x mar week 3	-0.311	(0.313)	-0.360	(0.228)
turnout x mar week 4	-0.391	(0.287)	-0.518	(0.335)
turnout x apr week 1	-0.273**	(0.136)	-0.484**	(0.212)
turnout x apr week 2	-0.288**	(0.134)	-0.454**	(0.227)
turnout x apr week 3	-0.305**	(0.127)	-0.458**	(0.208)
turnout x apr week 4	-0.309**	(0.123)	-0.460**	(0.202)

continued

Table C.5 continued

	(1)		(2)	
turnout x may week 1	-0.318***	(0.121)	-0.442**	(0.200)
turnout x may week 2	-0.297**	(0.120)	-0.427**	(0.198)
turnout x may week 3	-0.297**	(0.120)	-0.421**	(0.198)
turnout x may week 4	-0.296**	(0.119)	-0.423**	(0.197)
lower tier local authority FE	yes		yes	
NUTS1 x week FE	yes		yes	
controls x week FE	no		yes	
mean	3.159		3.159	
observations	3,284		3,284	
Panel D – Sweden				
turnout x march	-0.352	(0.220)	-0.398	(0.282)
turnout x april	-0.332*	(0.192)	-0.342	(0.254)
turnout x may	-0.403**	(0.187)	-0.617**	(0.257)
turnout x june	-0.427**	(0.188)	-0.634**	(0.267)
municipality FE	yes		yes	
NUTS3 x month FE	yes		yes	
controls x month FE	no		yes	
mean	3.532		3.532	
observations	569		569	

Notes: This table presents the regression results from our excess mortality regression for Italy, Great Britain, Sweden and the Netherlands in equation (3). Standard errors clustered at the municipality (lower tier local authority in Great Britain) level in parenthesis. Column (2) adds control variables interacted with time FE. Statistical significance denoted as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$