I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13310

Social Capital and the Spread of COVID-19: Insights from European Countries

Alina Kristin Bartscher
Sebastian Seitz
Sebastian Siegloch
Michaela Slotwinski
Nils Wehrhöfer

MAY 2020

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13310

Social Capital and the Spread of COVID-19: Insights from European Countries

Alina Kristin Bartscher
University of Bonn

Sebastian Seitz
ZEW and University of Mannheim

Sebastian Siegloch
ZEW, University of Mannheim and IZA

Michaela Slotwinski
ZEW and University of Basel

Nils Wehrhöfer
ZEW and University of Mannheim

MAY 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Social Capital and the Spread of COVID-19: Insights from European Countries*

We explore the role of social capital in the spread of the recent Covid-19 pandemic in independent analyses for Austria, Germany, Italy, the Netherlands, Sweden, Switzerland and the UK. Exploiting within-country variation, we show that a one standard deviation increase in social capital leads to 12% and 32% fewer Covid-19 cases per capita accumulated from mid-March until mid-May. Using Italy as a case study, we find that high-social-capital areas exhibit lower excess mortality and a decline in mobility. Our results have important implications for the design of local containment policies in future waves of the pandemic.

JEL Classification: D04, A13, D91, H11, H12, I10, I18

Keywords: COVID-19, social capital, collective action, health costs, Europe

Corresponding author:
Sebastian Siegloch
University of Mannheim
Department of Economics
L7, 3-5
68161 Mannheim
Germany

E-mail: siegloch@uni-mannheim.de

* This version is an update to the version from April 2020. We added results on excess mortality for Great Britain, the Netherlands and Sweden. We also included sensitivity checks for all countries. We thank Ulrich Glogowsky, Jarkko Harju, Jan Marcus, Andrew Oswald, Andreas Peichl, Kurt Schmidheiny, Felix Weinhardt, and seminar participants at the University of Mannheim for their helpful comments. Axel Franzen and Katrin Botzen generously shared their data on German associations with us. We are grateful to Elisa Casarin, Christian Hilscher and Dorian Weber, who provided excellent research assistance. Bartscher acknowledges funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany´s Excellence Strategy – EXC 2126/1– 390838866.

1 Introduction

The current Covid-19 pandemic has triggered a tremendous amount of research contributing to a better understanding of the virus and its containment. In absence of medical answers like pharmaceuticals or vaccines, human behavior is the key margin to contain the spread of the pandemic (Van Bavel et al., 2020). Hence, it is not surprising that policymakers and health experts around the world have been appealing to the social responsibility of their citizens, asking them to limit social contacts and follow strict hygiene and distance recommendations.[1] In other words, politicians urge their citizens to consider the social costs of their individual actions. Note that even if a vaccine is found, people's willingness to get vaccinated will likely depend on their civic norms and sense of responsibility (Chuang et al., 2015; Jung et al., 2013). We define this willingness to act collectively and pursue socially valuable activities as social capital (Putnam, 1993, 2000).[2]

While social capital plays a key role in official Covid-19 strategies around the globe, there is little systematic evidence on whether it is indeed an important factor in containing Covid-19 and affecting public health. In this paper, we provide important and timely evidence from independent analyses for seven European countries that social capital has a causal and positive effect on pandemic-related health outcomes. To the best of our knowledge, this is the first study to analyze the relationship between social capital and Covid-19 cases as well as excess deaths directly.

We operationalize social capital by area-specific electoral turnout in the 2019 European election, yielding a consistent and comparable measure across countries that has little measurement error and is likely to be largely unaffected by economic factors (Barrios et al., 2020; Putnam, 1993, 2000). We obtain very similar results when using alternative measures of social capital such as blood donations, registered organ donors, association density or historical literacy rates (Giuliano and Wacziarg, 2020; Guiso et al., 2004; Satyanath et al., 2017; Tabellini, 2010). We choose Covid-19 cases as our main outcome variable because it is available on a daily basis at a fine geographic level across many countries. To address potential issues of measurement error and endogeneity related to the number of reported cases, such as (non-random) differences in testing, we use log cumulative excess mortality as an alternative outcome for the Netherlands, Great Britain, Italy, and Sweden. Excess mortality is defined as the number of all deaths in a given time

[1] Some prominent examples are: Angela Merkel (18.03.2020): "This is the greatest challenge for our country since WWII, in which taking action collectively as a society is key." Emmanuel Macron (16.03.2020): "But the best rule is the rule that you, as citizens, impose on yourselves. Once again, I am appealing to your sense of responsibility and solidarity." Giuseppe Conte (26.04.2020): "The responsible conduct of every one of us will be fundamentally important. (...) If you love Italy, keep your distance."

[2] In this definition, sometimes also referred to as civic capital (Guiso et al., 2011; Lichter et al., 2020), we narrow down the broader concept of social capital to its positive facet of helping a group to overcome free rider problems, which fits best to the current Covid-19 crisis.

period relative to the average number for the same period in 2015-2019. We prefer the measure of excess mortality over Covid-19 deaths as a substantial number of people died without being tested during the current pandemic (Ciminelli and Garcia-Mandicó, 2020). Another advantage of looking at excess mortality is that we observe outcomes prior to the outbreak, giving rise to a standard differences-in-differences design and enabling us to test for differential pre-treatment trends.

As countries differ in many macroeconomic and Covid-19-specific aspects, it is challenging to identify the systematic effect of any economic or cultural factor from cross-country comparisons (Goodman-Bacon and Marcus, 2020). For this reason, we adopt a novel methodological approach and implement a within-country-across-countries research design. We probe the relationship between social capital and the spread of Covid-19 in independent analyses for seven European countries - Austria, Germany, Great Britain, Italy, the Netherlands, Sweden and Switzerland, implementing the same microeconometric within-country design in all seven countries. In each country, we regress the daily log cumulative Covid-19 cases or excess deaths on a measure of pre-determined social capital interacted with day fixed effects. The logarithmic model accounts for the exponential growth of the virus.[3] Our main empirical specification boils down to a two-way fixed effects model with area fixed effects and fine-grained time fixed effects capturing regional outbreak patterns and policy responses (region-by-day fixed effects) as well as different outbreak patterns over time (weeks-since-outbreak-by-day fixed effects). The large number of fixed effects is crucial for identification. Reassuringly, controlling for a host of important potential confounders like income, population density, age structure, education levels, hospital density or the share of white-collar workers has only marginal quantitative effects on our estimates. This result is confirmed by an application of the bounding exercise suggested by Oster (2019).

From a theoretical perspective, social capital, the spread of Covid-19 and containment policies interact in various ways. First, high-social-capital areas are known to be more vibrant and better connected, both economically and socially (see, e.g., Bai et al., 2020; Knack and Keefer, 1997; Tabellini, 2010). Hence, we expect the virus to spread more quickly in those areas in the beginning of the pandemic, when information about the disease and its severity were incomplete. Second, as soon as the importance of behavioral containment norms becomes more salient, we expect the relationship to change. Complying with containment norms yields a classical collective action problem (Ostrom, 1991): it is costly for the individual, while the single individuals' contribution to the collective goal is negligible. Social capital is assumed to overcome exactly such problems by increasing the willingness to contribute to the common good (Coleman, 1990; Ostrom, 1999; Putnam, 1993, 2000). Hence, we expect that informal rules of containment are more likely to

[3] Additionally, Goodman-Bacon and Marcus (2020) point out that a log model helps to difference out measurement error in the outcome variable.

be (voluntarily) adopted in areas with high social capital, leading to a relative decrease in infections. Third, there are interactions with the strictness of containment policies. During lockdowns, rules are formalized and violations are easier to detect and to be sanctioned, making non-compliance more costly for the individual. Hence, we would expect containment to depend less on social capital during stricter policy regimes.

We derive the following main findings. First, we find that high-social-capital areas accumulated between 14% and 40% fewer Covid-19 cases between mid-March and end of June. Likewise, high-social-capital areas also exhibit between 7% and 14% less excess deaths in Great Britain, the Netherlands, Italy, and Sweden. A one standard deviation increase in social capital could have prevented between 459 deaths in Sweden and 8,800 deaths in Great Britain. Second, we find qualitatively similar patterns across all independently analyzed countries, which we regard as strong evidence for the robustness of our empirical results. Third, we show a consistent dynamic pattern: the number of Covid-19 cases is initially higher in high-social-capital areas. However, as information on the virus spreads, high-social-capital areas start to show a slower increase in Covid-19 cases in all seven countries. The role of social capital diminishes as soon as national lockdowns are enforced. Last, our results also hold if we exploit alternative measures of social capital, and are robust to the inclusion of an extensive set of fixed effects and a host of obvious potential confounders. We further provide evidence that our results are unlikely to be driven by unobserved confounders.

This is the first paper to look at the role of social capital for health outcomes in a pandemic, as measured by Covid-19 cases and excess mortality, across different countries. Our results complement an exploding literature studying the relationship between social capital and mobility. These studies show that social capital affects mobility, which is arguably the type of socially responsible behavior that can be measured best. For the U.S., several studies show that citizens in counties with high social capital reduce mobility more than those in low-social-capital counties (Bai et al., 2020; Borgonovi and Andrieu, 2020; Brodeur et al., 2020; Ding et al., 2020). Barrios et al. (2020) show for U.S. counties and European regions[4] that individuals in regions with higher measures of civic duty voluntarily reduced their mobility more strongly in the early stages of the pandemic. Bargain and Aminjonov (2020) find similar results for European regions, and Durante et al. (2020) for Italian and German areas.

Our findings reinforce these results in two ways. First, we show that changes in behavior translate into health outcomes, which confirms the implied theoretical mechanism as well as the advice given by policymakers and health experts around the globe. Second, our findings suggest that socially responsible behavior is particularly important in the absence of containment policies or when soft containment policies like hygiene or stay-

[4] Our analyses for European countries operate at a lower geographical level, which enables us to include region fixed effects.

at-home recommendations are in place. Our dynamic estimates show that the role of social capital is reduced as soon as strict European-style lockdowns are implemented. This is in line with macro-level evidence that countries with democratically accountable governments introduced less stringent lockdowns, but were more effective in reducing geographic mobility at the same level of policy stringency (Frey et al., 2020). In this respect, our study is also related to the branch of the current Covid literature analyzing the effects of different containment policies (see, e.g., Engle et al., 2020; Friedson et al., 2020; Glogowsky et al., 2020; Painter and Qiu, 2020).

More generally, our findings contribute to the literature on the importance of social capital for society. It is well-established that higher social capital has positive economic, social and political effects (see, e.g., Glaeser et al., 1996; Goldin and Katz, 1999; Guiso et al., 2004; Knack and Keefer, 1997; Nannicini et al., 2013; Tabellini, 2010). In terms of health outcomes, the meta-analysis by Xue et al. (2020) confirms that social capital has a positive, but typically small impact on the incidence of diseases. However, the considered studies mostly focus on non-communicable diseases such as cancer, heart disease or diabetes. We show the important role of social capital during an acute medical crisis with a very contagious virus.

In the light of possible future Covid-19 waves, our findings have important implications for policymakers. As regional turnout is easily observable, local policy makers can consider this proxy when determining the strictness of local containment policies, trading off the economic consequences of a lockdown against infection risks. Moreover, given findings from the medical literature which indicate a positive association between social capital and the willingness to get vaccinated (Chuang et al., 2015; Jung et al., 2013; Rönnerstrand, 2014), this proxy can help to assess the expected effectiveness of vaccination campaigns once a vaccine is found.

The remainder of the paper is structured as follows. Section 2 summarizes our data and provides first descriptive evidence. In Section 3, we set-up our econometric model and describe our identification strategy. Section 4 presents our key empirical results together with an extensive sensitivity analysis. Section 5 concludes.

2 Data, Institutions and Descriptive Evidence

In the following, we briefly describe the variables used in the empirical analysis. More information and detailed data sources are documented in Table A.1.

2.1 Variables and Sources

We use publicly available data on health and social capital from seven European countries that publish the daily number of total Covid-19 infections at fine-grained geographical levels. We compile measures of the spread of Covid-19 and social capital at the finest geographical level available for each country. We refer to this unit of observation as "area" throughout the paper. Areas have different names across countries, but mostly refer to the NUTS3 definition of the European Union (see Table A.3).[5] We refer to the higher NUTS1 geographical level as regions.

Outcomes. For all countries, we obtain the daily number of Covid-19 cases since the early phase of the outbreak. The respective country samples start when more than 90% of all NUTS3 areas in a country have registered at least one official case. Our main outcome variable is the log cumulative number of confirmed Covid-19 infections per 100,000 inhabitants within an area on a given day. Figure A.1 shows the evolution of cumulative Covid-19 cases per 100,000 inhabitants at the national level across countries.

For Great Britain, the Netherlands, Italy and Sweden, we additionally use data on the number of excess deaths. For other countries, comparable data was not available at the necessary level of geography. Excess mortality measures the number of deaths in a given period minus the average number of deaths in the same period in the years between 2015 and 2019. The Netherlands only publishes data for 2019 and 2020, Sweden for 2018 until 2020. The evolution of daily excess mortality per 100,000 inhabitants at the national level until May 2020 is plotted in Figure A.2.

Social capital. In our main specification, we operationalize social capital by voter turnout in the 2019 European Parliament election. Political participation is a frequently-used and well-established measure of social capital, or civicness (Putnam, 1993, 2000). An extensive literature documents that political participation is a strong correlate of pro-social preferences and the willingness to contribute to public goods (see, e.g., Bolsen et al., 2014; Dawes et al., 2011; Fowler, 2006; Fowler and Kam, 2007; Jankowski, 2007). Turnout is unlikely to be driven by other economic and legal factors and should have little to no measurement error (Guiso et al., 2004). In the context of our study, we can use data from the same election in all but one country. For Switzerland, we use data on turnout at the last national elections in 2019.

As a sensitivity check, we use alternative measures of social capital proposed in the literature (Guiso et al., 2004; Putnam, 1993). We exploit data on blood donations and

[5] In the Netherlands (municipality level), Great Britain (lower tier local authority level) and Austria (district level), we have data on even finer levels. The NUTS system is based on existing national administrative subdivisions. The average population size within a NUTS3 area in a country is typically between 150,000 and 800,000 inhabitants.

registered organ donors per capita for countries where it is available at a fine geographical level (Italy, the UK, Switzerland, the Netherlands). As this data is not systematically available for Germany, we use instead the number of all registered associations following the work by Buonanno et al. (2009), Giuliano and Wacziarg (2020), and Satyanath et al. (2017). Last, we also make use of measure of historical literacy rates in Italy following Tabellini (2010) (see Section 4.2).

Controls. We test the sensitivity of our results to potential confounders by controlling for the share of white-collar workers, the share of the population older than 65 years, the share of educated individuals, the number of hospitals per capita, log GDP per capita, and the population density (see Tables A.1 and A.2 for details and descriptive statistics). We were able to collect the same set of control variables for all seven countries under study.

2.2 Policy responses and timing of effects

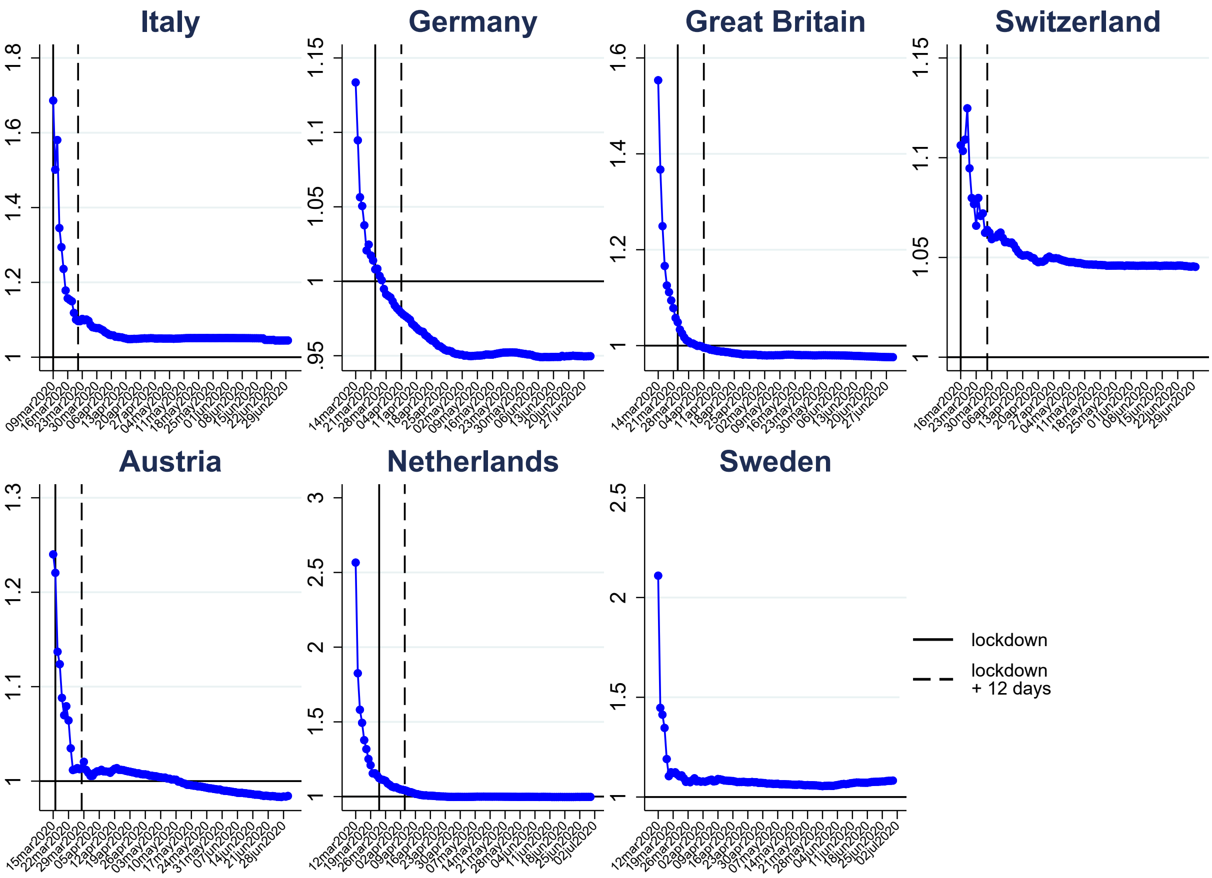
The timing of the Covid-19 outbreak and policy responses differ across countries. Moreover, the adopted policy measures vary in strictness. While Italy enforced a strict and long lockdown, Sweden has not adopted a lockdown so far. Eventually, six of the seven countries under study implemented a national lockdown, which was stricter than comparable U.S. safer-staying-at-home declarations. We highlight the most important events in each country in Table A.4.

Any change in behavior or policy will affect the number of Covid-19 cases with a lag. First, there is the incubation time, which is the time from the infection until the appearance of first symptoms. Second, there is the confirmation time, which is the time between the first symptoms and the medical confirmation of the case. Naturally, both periods differ across individuals, time and countries. For incubation time, we follow the WHO and assume a duration of 5 days (Lauer et al., 2020). There is much less evidence on confirmation time. We assume that the confirmation time is 7 days, using the reported median duration from a study by the official German health agency RKI (Heide and Hamouda, 2020). In total, we conclude that any behavioral change will affect Covid-19 cases after around 12 days.

2.3 Descriptive evidence

In a first step, we investigate the raw, descriptive pattern of the spread of Covid-19 and its relation to social capital across countries. We dichotomize social capital into high-social-capital (above-regional-median turnout) areas and low-social-capital (below-regional-median turnout) areas for each country. We define the ratio of the number of log cases per capita in high- relative to low-social-capital areas within each region

Figure 1: Cumulative Covid-19 cases in high relative to low-social-capital areas



Notes: This figure shows the ratio of log cumulative Covid-19 cases per capita in high- vs. low-social-capital areas. The sample is divided at the median of turnout at the NUTS1 region level. Areas with a value above the median are defined as high-social-capital areas and those below as low-social-capital areas. The blue lines plot the population-weighted average of the regional log ratios over time. The solid black line marks the date of the national lockdown, the dashed black line the date of the national lockdown plus an incubation period of 12 days.

and calculate the population-weighted average of this ratio across regions to obtain the national ratio.

Figure 1 plots the log cumulative Covid-19 cases per capita in high-social-capital areas relative to low-social-capital areas over time. Across all countries, we see that the virus is initially more prevalent in high-social-capital areas. The initially high level is to be expected as people in areas with a high level of social capital have been shown to have closer social and economic connections, which should exacerbate the spread of the virus initially when information on the severity of the virus and appropriate behavior are incomplete (see, e.g., Bai et al., 2020; Borgonovi, Andrieu, and Subramanian, 2020; Knack and Keefer, 1997; Tabellini, 2010). Starting from this high initial level, we then see a sharp decline in the ratio. Over time, the ratio drops until high-social-capital areas have less than or almost equally many cases per inhabitant as low-social-capital areas. The decline starts before national lockdown policies could have been effective. This is a first indication that socially responsible behavior might play a role.

3 Empirical model and identification

While Figure 1 presents simple correlations over time, we suggest the following more rigorous empirical model to study the evolution of the relationship between social capital and the spread of the virus in each country systematically:

$$\ln cumcases_{ard} = \sum_{d=2}^{d^{max}} \beta_d date_d \cdot SocCap_a + \gamma_a + \omega_{rd} + \varepsilon_{ard}. \quad (1)$$

Our main outcome variable $\ln cumcases_{ard}$ is the log cumulative number of cases per 100,000 inhabitants in area a within region r on day d. The logarithmic model accounts for the exponential growth of the virus. Moreover, Goodman-Bacon and Marcus (2020) point out that a log model helps to difference out measurement error in the outcome variable.

The variable $SocCap_a$ is our measure of social capital. In the baseline specification, we proxy for social capital with area-specific turnout in the European Parliament election of 2019, normalized by its country-specific standard deviation. Hence, a one-standard-deviation increase in turnout (social capital) affects the number of cumulative cases per 100,000 inhabitants measured on day d by approximately $100 \times \beta_d\%$. The indicator variable $date_d$ is set to one for the respective day, and else zero. Our sample starts when more than 90% of all NUTS3 areas have registered at least one official case, and ends on d^{max}. The indicator variable γ_a captures area fixed effects, which account for time-invariant, area-specific factors. Given the area fixed effects, we normalize the coefficient β_1 to zero in all countries, such that all other β_d coefficients measure the effect of social capital relative to this reference day. The β coefficients compare the evolution of areas with a higher turnout to areas with a lower turnout over time and associate the differences in log cases with the level of social capital. Loosely speaking, the empirical model (1) investigates the slope of the country-specific patterns shown in Figure 1.

The set of dummy variables ω_{rd} captures NUTS1-region-specific day fixed effects and hence flexibly accounts for potential policy responses at the regional level and region-specific dynamics in the spread of the virus. We cluster standard errors at the area level.

Our identifying assumption is that no other factor correlated with social capital systematically affects growth rates of Covid-19 cases. While this assumption is untestable, we adopt the following two-step approach to show that the identifying assumption is likely to hold.

First, we include a very detailed and rich set of fixed effects. Our region-by-day fixed effects ω_{rd} capture regional outbreak patterns and policy responses. Hence, our effect is identified within a region.[6] Another concern is that the time of an outbreak in an area

[6] Note that the variation in most other European studies is at this regional level.

varies. Area A might have an earlier outbreak than area B and consequently be on a different point of the outbreak curve. To account for this, we add weeks-since-outbreak fixed effects to the baseline model, which implicitly synchronize the outbreak dates of the areas by accounting for the average pattern of an outbreak across areas. As information about Covid-19 spread quickly, it is possible that outbreak patterns change over time, so we additionally augment the set of weeks-since-outbreak fixed effects by interacting it with calendar-day fixed effects ($date_d \times weekssinceoutbreak_{ad}$).

Despite the large set of fixed effects, there might still be the concerns that that some area-specific confounders drive the results. In the second step, we therefore add the most obvious confounding variables to the baseline model in all seven countries: (i) education (more skilled people understand more quickly what is at stake); (ii) age (older people are more endangered by the virus); (iii) GDP per capita (higher-income groups can afford to reduce their labor supply more); (iv) occupation type (white-collar workers can work from home more easily) (v) population density (facilitates the spread of the disease) and (vi) hospital density (better medical infrastructure helps to fight the virus). We use a pre-outbreak measure of the respective confounders and interact each covariate with day-fixed effects.

Comparing point estimates of the baseline model (1) with the enhanced models including controls and/or fixed effects gives an indication of whether the identifying assumption holds. If point estimates are relatively stable, even if we flexibly control for very likely confounders like GDP, this is a first indication that unobserved potential confounders are unlikely to bias our estimates in a meaningful way. We further use the test suggested by Oster (2019) to show that our estimates are unlikely to be overturned by unobserved confounders.

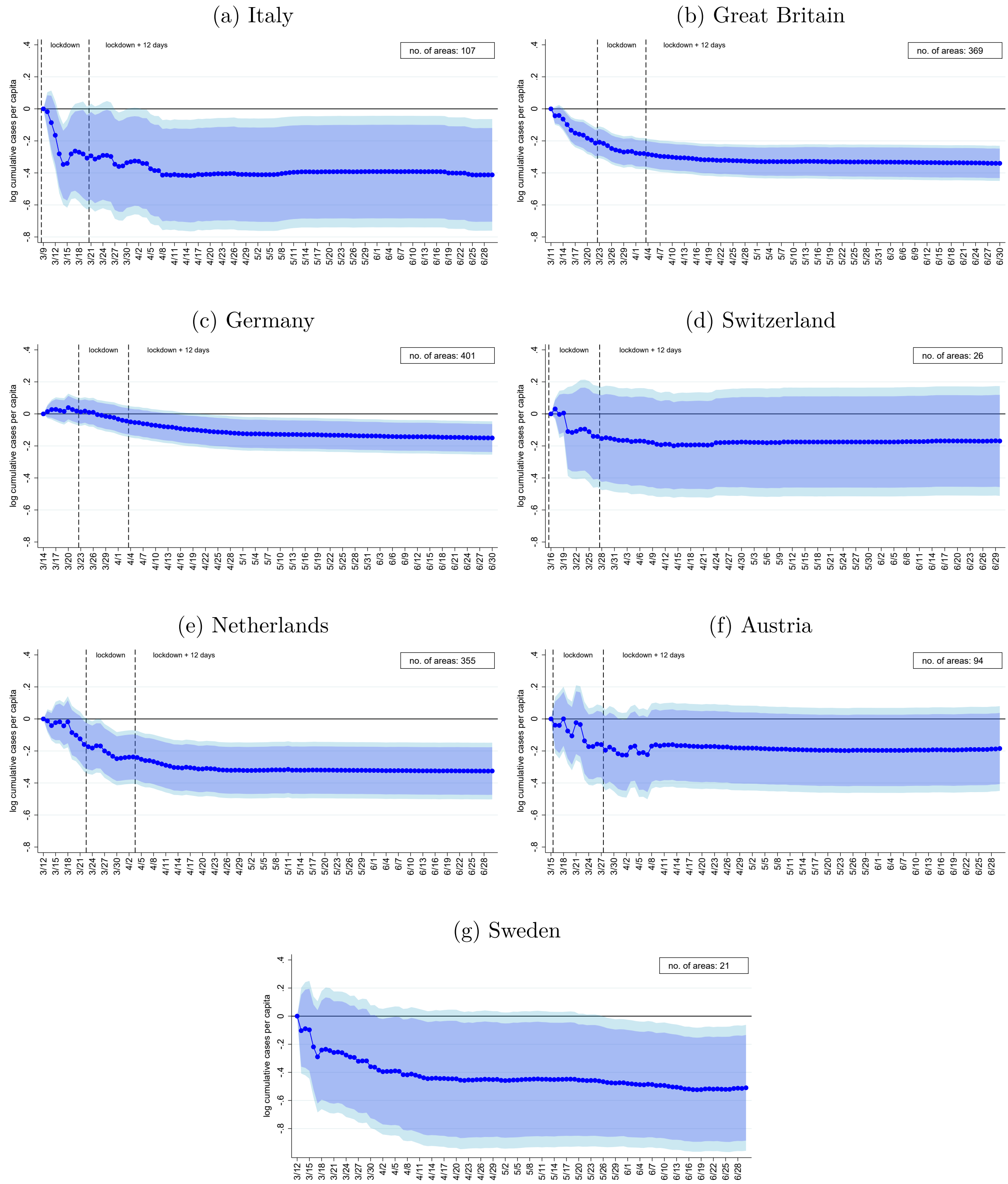
An alternative test of the identifying assumption arises when looking at excess deaths. While there is obviously no meaningful pre-treatment period for Covid-19 cases, we can exploit information on excess mortality from the period prior to the pandemic. This enables us to test for parallel pre-Covid trends. As a downside, data on excess mortality at a fine geographical level is only available for Italy, Great Britain, the Netherlands and Sweden.

4 Empirical findings

4.1 Main results

Figure 2 visualizes the β coefficients from equation (1). Across all countries, we see a similar pattern: high-social-capital areas exhibit a slower growth of cumulative cases than low-social-capital areas. This reduces the cases they accumulate over the considered

Figure 2: Effect of social capital on the spread of Covid-19 cases



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 on the model outlined in equation (1) (see Table B.2 for the point estimates). All values are normalized at the date of the first observation. 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. 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.

periods by between 14% (Germany) to 40% (Sweden). Results are significant at the 95% level for Italy, Great Britain, the Netherlands, Germany and Sweden. Effects are not significant at conventional levels for Austria and Switzerland. A likely explanation for this is the relatively small number of areas, as indicated in the top right corner of the panels, in combination with the large number of fixed effects that are already included in the baseline model. Nevertheless, the dynamic point estimates in Austria and Switzerland look very similar to the effects estimated for the other countries.

Overall, we interpret the consistent pattern obtained from independent analyses of seven countries as strong evidence in favor of the hypothesis that social capital plays an important role in slowing down the spread of the virus.

Our empirical event-study model enables us to study the dynamics of the effect of social capital in detail. Figure 2 clearly shows that areas with high social capital exhibit a slower growth in Covid-19 cases in the early phase of the pandemic. Importantly, the responses occur before the national lockdowns could have had an effect: assuming an incubation plus confirmation time of about 12 days (cf. Section 2.2), Figure 2 shows large fractions of the long-term effect have been materialized before the 12 days lag after the national lockdown.

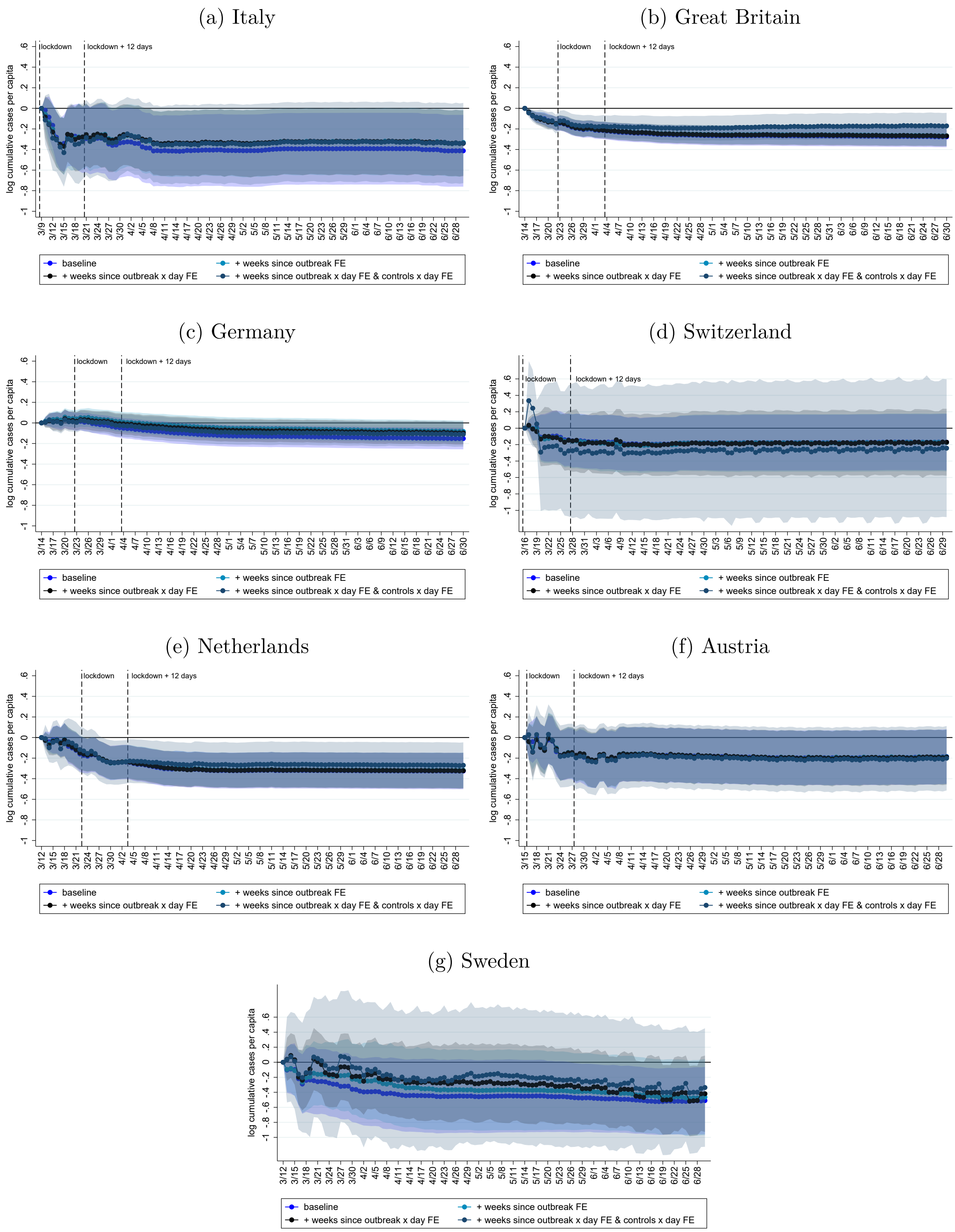
It is exactly during this initial phase of the pandemic that we expect the impact of social capital to be strongest, as responsible individual behavior such as distancing, wearing masks, washing hands or reducing mobility is the only means to flatten the curve. After national lockdowns take effect, the growth differential in Figure 2 between low- and high-social capital areas stabilizes. This point is further reinforced by the Swedish results. Despite being the only country that did not implement a national lockdown, the estimate is very similar to the other countries.

4.2 Sensitivity

In the following, we test the sensitivity of our main results along various dimensions.

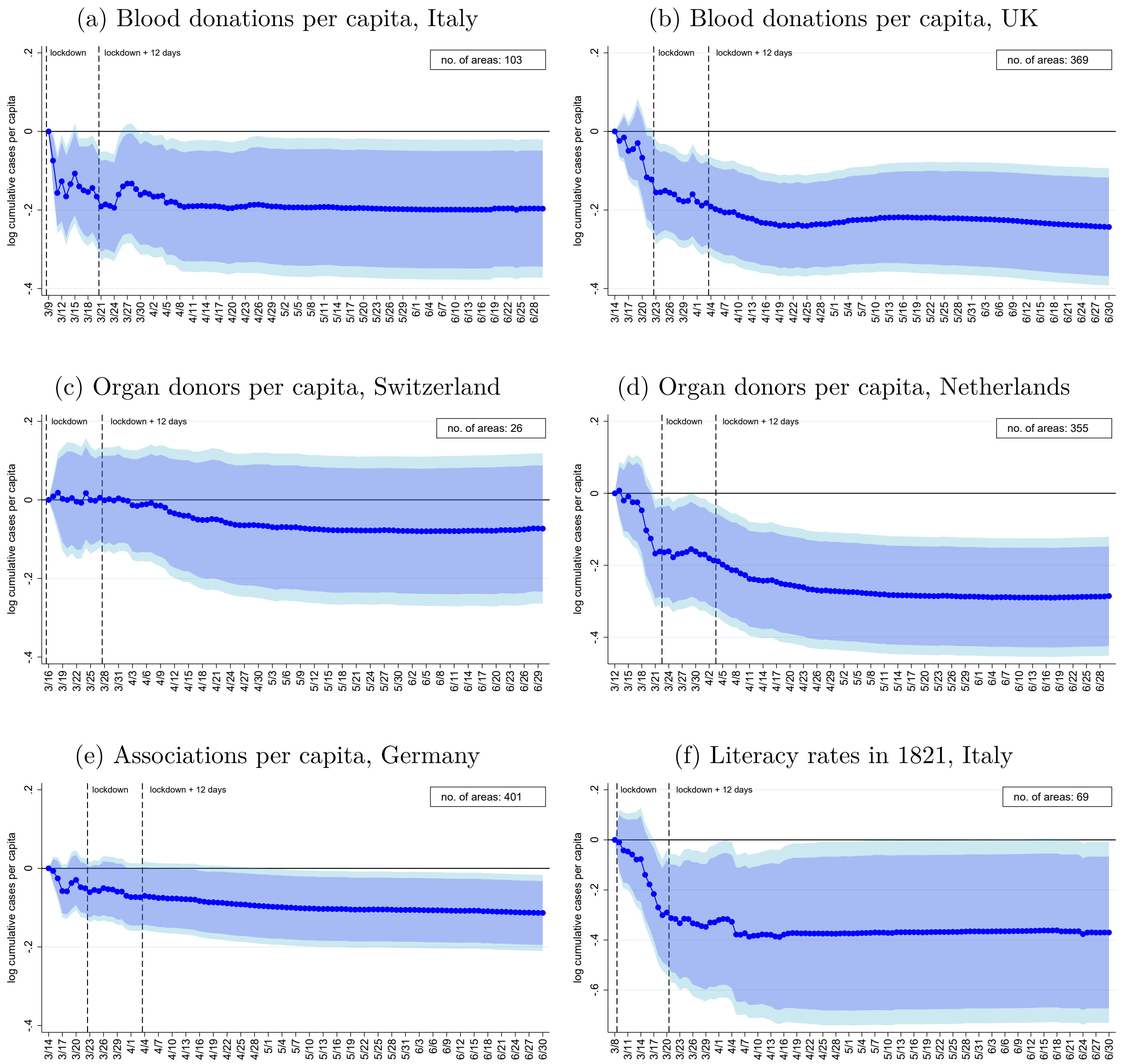
Confounding variables. One concern is that measures of social capital like voter turnout might be correlated with other Covid-19-related characteristics. If this correlation were similar across the seven countries, we would wrongly attribute the effects to social capital. Hence, we have to make sure that the observed relationship between Covid-19 cases and social capital is not driven by such factors. As discussed in Section 3, we test the sensitivity of our results by adding (i) different sets of fixed effects and (ii) obvious confounding variables interacted with day fixed effects to our baseline model (1).

Figure 3: Effect of social capital on cases with additional fixed effects and controls



Notes: This graph shows alternative specifications for the results reported in Figure 2. The dark blue line reports the baseline results in Figure 2 (see Appendix Table B.2 for point estimates). 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. The first vertical dashed line marks the date of the national lockdown in each country. The second vertical dashed line corresponds to the date of the national lockdown plus 12 days, which accounts for incubation plus confirmation time. The shaded areas report the 95% confidence intervals.

Figure 4: Alternative social capital measures



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 (1) and the outcome variable is the log cumulative number of Covid-19 infections per 100,000 inhabitants. In panels (a) and (b) we use blood donations per capita as our proxy for social capital, in panels (c) and (d) we use the number of registered organ donors per capita as a proxy, in panel (e) we use associations per capita, in panel (f) literacy rates in 1821 (see Table B.3 for point estimates).

Figure 3 shows the resulting estimates. Magnitudes, dynamics and statistical significance are generally very similar across specifications, which is a first indication that further unobserved confounders are unlikely to drive the results.[7]

To assess the role of unobserved confounders more formally, we also implement the method suggested by Oster (2019), which additionally takes into account movements in the R-squared across specifications. We apply the suggested bounding exercise to the last point estimate $\beta_{d^{max}}$ of our dynamic model (1). Appendix Table B.1 shows that all bounded estimates stay negative when assuming that unobservables are as important as the observables in explaining the effects ($\delta = 1$). In other words, the table suggests that our findings are robust to omitted variable bias, e.g. due to fear of infection.[8]

Alternative social capital measures While using electoral turnout is a standard measure of social capital, which seems particularly suited in the context of our study due to its availability and comparability across countries, we assess the sensitivity of our results with respect to alternative social capital measures. The literature has validated blood or organ donations as useful proxies of social capital (see, e.g., Guiso et al., 2004; Putnam, 1993). For Italy and Britain, we could obtain sufficiently fine-grained data on blood donations. For Switzerland and the Netherlands, we could obtain data on the number of registered organ donors who are willing to donate (see Table A.1 for details). Panels (a) to (d) of Figure 4 show that the results are similar when using these alternative measures of social capital.

For Germany, no centralized evidence on the number of blood donations or registered organ donors is available. As an alternative, we use the density of associations in the area, a widely used proxy, which is has been shown to be correlated with membership rates (Putnam, 2000; Satyanath et al., 2017). Panel (e) shows a very similar effect on Covid-19 cases, when using this proxy. Last, the literature on social capital frequently studies the case of Italy, because there is large variation in social capital that can be attributed to historical origins (see, e.g., Nannicini et al., 2013; Putnam, 2000). It is well established that culture, and thus also cultural traits like social capital, are passed on from generation to generation and are thus quite persistent over time (Alesina et al., 2013; Bisin and Verdier, 2000; Tabellini, 2008). Following the rationale of Tabellini (2010), we use province-level literacy rates from Italy in 1821 as another, historical proxy for social capital, using data from Ciccarelli and Weisdorf (2018).[9] Panel (f) of Figure 4

[7]For better readability of the precision across specifications, Appendix Table B.2 reports the last dynamic estimate for each country with standard errors for each specification.

[8] Note that other studies show that fear cannot explain the association between changes in mobility and social capital in the current pandemic. Barrios et al. (2020) show this based on self-collected survey data from the U.S. Durante et al. (2020) get to the same conclusion using the distance to regional hotspots as a proxy for fear.

[9] As we operate at the NUTS3 level, we could not use the data in Tabellini (2010), which cover NUTS1 or NUTS2 regions across Europe. We transformed our data to the province borders of 1911 (see Table

again shows a very similar pattern. Appendix Figure B.1 confirms that these results are again robust to the inclusion of additional fixed effects and controls.

Excess mortality If higher social capital slows down the spread of Covid-19 cases, we would also expect to see an effect on the number of Covid-19-related deaths. Our preferred measure of mortality is the number of local excess deaths per 100,000 inhabitants (Aron and Muellbauer, 2020; Ciminelli and Garcia-Mandicó, 2020), defined as the difference in mortality between 2020 and the average between 2015 and 2019.[10] We prefer this measure of mortality over official Covid-19 deaths, as the latter measure is likely to underestimate the true increase in mortality, since a substantial number of people died without being tested (Ciminelli and Garcia-Mandicó, 2020).

While looking at mortality is important in its own right, it is also insightful in terms of identification as (i) the number of deaths should depend less on testing capacities, which might in turn be endogenous to social capital[11] and (ii) excess mortality – in contrast to the number of Covid-19 cases – is observable already before the start of the pandemic. This enables us to evaluate the common trend assumption as in a standard difference-in-difference model and test for pre-treatment differences between high- and low-social-capital areas.

Data on excess deaths are, to date, available at a fine geographic level for four countries in our sample: the Netherlands, Great Britain, Italy and Sweden.[12] For Italy, Sweden and the Netherlands, excess mortality is available at the municipal level, allowing us to estimate equation (1) with log cumulative number of excess deaths per 100,000 inhabitants as our outcome variable while additionally controlling for NUTS3-by-time FE.[13]

Figure 5 shows that by the end of May, a one standard deviation increase in turnout is significantly associated with fewer accumulated excess deaths per 100,000 inhabitants in the Netherlands, Great Britain, Italy and Sweden. The effect size ranges from 7% in Italy to 16% in Great Britain. These estimates suggest that a one standard deviation increase in social capital could have prevented 459 deaths in Sweden, 1,151 deaths in the Netherlands, 2,413 deaths in Italy and 8,840 deaths in Great Britain. Reassuringly, mortality before the pandemic evolved in parallel between high- and low-social-capital areas, which lends support to our identifying assumption.

In terms of dynamics, Figure 5 corroborates the evidence shown in Figures 1 and 2: the

A.1 for details).

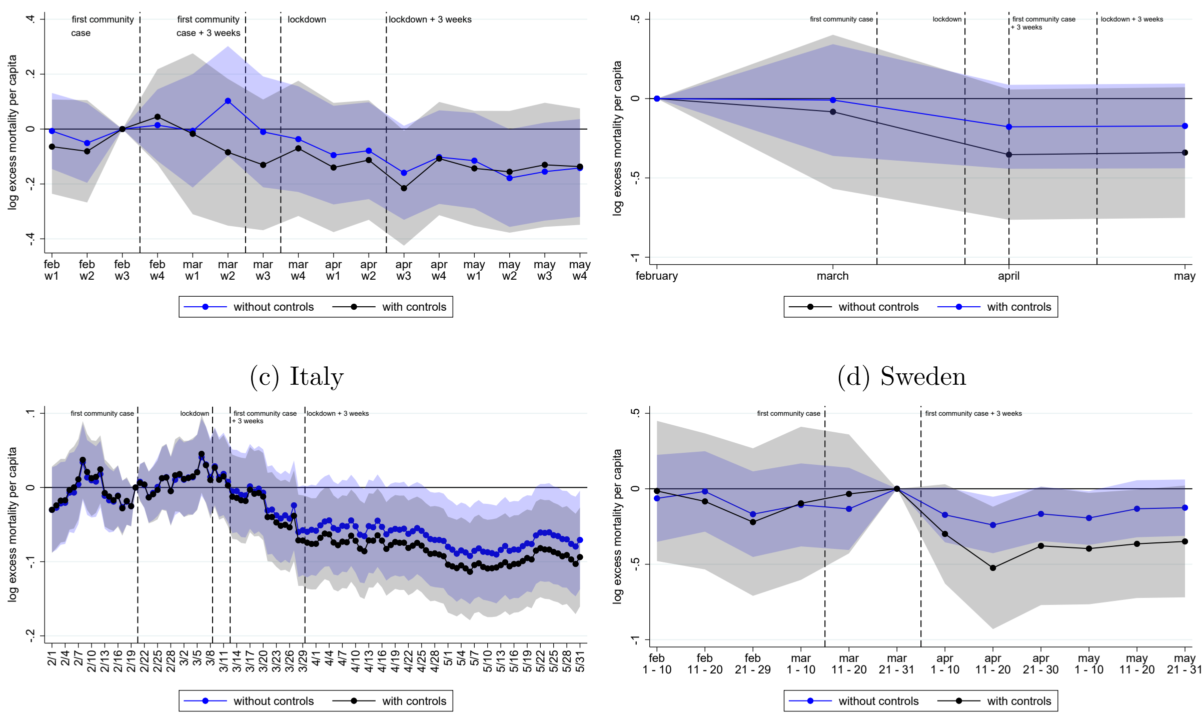
[10] For the Netherlands, we could only obtain mortality data for 2019 and 2020. Sweden published data for 2018, 2019 and 2020.

[11] Mortality is not completely immune to that concern, as more testing might imply more effective isolation of infected individuals.

[12] Germany, Switzerland and Austria only publish mortality data at higher levels.

[13] Since excess mortality is only available at the Lower Tier Local Authority-level in Great Britain, we use the same fixed effects as in equation (1) in this case. Note that the data for all of Great Britain is only available on a monthly basis.

Figure 5: Effect of social capital on excess deaths



(a) Netherlands (b) Great Britain (c) Italy (d) Sweden

Notes: The outcome variable is the log number of excess deaths per 100,000 inhabitants from February to May 2020 (see Appendix Table B.4 for the point estimates). The shaded areas correspond to 95% confidence intervals.

number of excess deaths in high-social-capital areas starts to drop around the time of (or even before) the national lockdown. This trend break cannot be driven by the lockdown due to the incubation time and the duration of the disease before it leads to fatalities. Instead, we find that excess mortality drops in high-social-capital areas about two to three weeks after the first community case was discovered, which is in line with (preliminary) evidence that deaths tend to occur around three weeks after the infection (Yang et al., 2020). The effect of social capital on excess deaths stabilizes around two to three weeks after the lockdown.This suggests again that the additional effect of social capital is limited once lockdowns are in place.

5 Conclusion

In this paper, we provide evidence from seven European countries that culture and social capital have a considerable impact on the containment of Covid-19 and the number of deaths. Social capital, long known to be related to favorable economic developments, can thus unfold additional potential in times of (health) crises, which call for collective action and socially responsible behavior. The positive effects of social capital are likely to go beyond health outcomes. Experience from the Spanish Flu demonstrates that a successful virus containment directly relates to the size of the following economic downturn and its recovery speed (Barro, 2020; Barro et al., 2020). Hence, we expect that a higher level of social capital also has an indirect positive effect on the economy during and after the crisis.

Our results have important implications for policymakers. During the current crisis, our findings suggest that low-social-capital areas might need to consider stricter formal policies to contain the virus. Since turnout rates are readily observable, they could be directly targeted when designing the local policy response to Covid-19. The policy shift in Germany that delegated more responsibility to the county level might be a good way to allow for this regional flexibility, especially with the looming threat of a second outbreak in the fall or winter. Importantly, social capital is likely to remain important even when a vaccine becomes readily available because the willingness to get vaccinated is a public good just as the willingness to practice social distancing. Consistently, evidence from the medical literature suggest that people in high-social-capital areas are more willing to get vaccinated (Chuang et al., 2015; Jung et al., 2013; Rönnerstrand, 2014).

In the longer run, investing in social capital formation is an important insurance against similar future pandemics. The insights from our study mandate policymakers to invest not only in the health system, but also in social capital formation to be well prepared. Possible points of departure are social components in transfer programs, or local community programs to increase social interactions, which may carry over to increased cooperation and pro-social behavior (see, e.g., Attanasio et al., 2015; Fearon et al., 2009; Feigenberg et al., 2010). However, investments should not be limited to low-social-capital areas. This is in particular true since pandemics might themselves erode social capital (Aassve et al., 2020).

References

Aassve, Arnstein, Guido Alfani, Francesco Gandolfi, and Marco Le Moglie (2020). *Epidemics and Trust: The Case of the Spanish Flu*. Working Papers 661. IGIER (Innocenzo Gasparini Institute for Economic Research), Bocconi University.

Alesina, Alberto, Paola Giuliano, and Nathan Nunn (2013). “On the origins of gender roles: Women and the plough”. In: *The Quarterly Journal of Economics* 128.2, pp. 469–530.

Aron, Janine and John Muellbauer (2020). “Measuring excess mortality: The case of England during the Covid-19 Pandemic”. In: *INET Oxford Working Paper*.

Attanasio, Orazio, Sandra Polania-Reyes, and Luca Pellerano (2015). “Building social capital: Conditional cash transfers and cooperation”. In: *Journal of Economic Behavior and Organization* 118. Economic Experiments in Developing Countries, pp. 22–39. ISSN: 0167-2681. DOI: https://doi.org/10.1016/j.jebo.2015.04.004. URL: http://www.sciencedirect.com/science/article/pii/S0167268115001080.

Bai, John Jianqiu, Wang Jin, and Chi Wan (2020). “The Impact of Social Capital on Individual Responses to COVID-19 Pandemic: Evidence from Social Distancing”. In: *Working Paper*.

Bargain, Olivier and Ulugbek Aminjonov (2020). “Trust and Compliance to Public Health Policies in Times of COVID-19”. In: *IZA Discussion Paper*.

Barrios, John M, Efraim Benmelech, Yael V Hochberg, Paola Sapienza, and Luigi Zingales (2020). “Civic capital and social distancing during the covid-19 pandemic”. In: *National Bureau of Economic Research*.

Barro, Robert J. (2020). “Non-Pharmaceutical Interventions and Mortality in U.S. Cities during the Great Influenza Pandemic, 1918-1919”. In: *NBER Working Paper Series* 27049, pp. 1–19.

Barro, Robert J., José F Ursúa, and Joanna Weng (2020). “The Coronavirus and the Great Influenza Pandemic: Lessons from the "Spanish Flu" for the Conoravirus’s Potential Effects on Mortality and Economic Activity”. In: *NBER Working Paper Series* 26866, pp. 1–27.

Bisin, Alberto and Alberto Verdier (2000). “Beyond the Melting Pot: Cultural Transmission, Marriage, and the Evolution of Ethnic and Religious Traits”. In: *The Quarterly Journal of Economics* 115.3, pp. 955–988. URL: http://www.jstor.org/stable/2586900.

Bolsen, Toby, Paul J. Ferraro, and Juan Jose Miranda (2014). “Are Voters More Likely to Contribute to Other Public Goods? Evidence from a Large-scale Randomized Policy Experiment”. In: *American Journal of Political Science* 58.1, pp. 17–30.

Borgonovi, Francesca and Elodie Andrieu (2020). “Bowling together by bowling alone: Social capital and Covid-19”. In: *Covid Economics* 17, pp. 73–96.

Borgonovi, Francesca, Elodie Andrieu, and S.V. Subramanian (2020). “Community level social capital and COVID-19 infections and fatality in the United States”. In: *Covid Economics* 32, pp. 110–126.

Brodeur, Abel, Idaliya Grigoryeva, and Lamis Kattan (2020). *Stay-at-Home Orders, Social Distancing and Trust*. GLO Discussion Paper Series 553. Global Labor Organization (GLO). URL: https://ideas.repec.org/p/zbw/glodps/553.html.

Buonanno, Paolo, Daniel Montolio, and Paolo Vanin (2009). “Does social capital reduce crime?” In: *The Journal of Law and Economics* 52.1, pp. 145–170.

Chuang, Ying-Chih, Ya-Li Huang, Kuo-Chien Tseng, Chia-Hsin Yen, and Lin-hui Yang (Apr. 2015). “Social Capital and Health-Protective Behavior Intentions in an Influenza Pandemic”. In: *PLOS ONE* 10.4, pp. 1–14. DOI: 10.1371/journal.pone.0122970. URL: https://doi.org/10.1371/journal.pone.0122970.

Ciccarelli, Carlo and Jacob Weisdorf (2018). “Pioneering into the past: Regional literacy developments in Italy before Italy”. In: *European Review of Economic History* 23.3, pp. 329–364. DOI: 10.1093/ereh/hey014. eprint: https://academic.oup.com/ereh/article-pdf/23/3/329/30622302/hey014.pdf. URL: https://doi.org/10.1093/ereh/hey014.

Ciminelli, Gabriele and Sílvia Garcia-Mandicó (2020). “COVID-19 in Italy: An Analysis of Death Registry Data”. In: *Working Paper*.

Coleman, James S. (1990). *Foundations of Social Theory*. Cambridge, MA: Harvard University Press.

Dawes, Christopher T., Peter John Loewen, and James H. Fowler (2011). “Social Preferences and Political Participation”. In: *The Journal of Politics* 73.3, pp. 845–856.

Ding, Wenzhi, Ross Levine, Chen Lin, and Wensi Xie (2020). “Social Distancing and Social Capital: Why US Counties Respond Differently to COVID-19”. In: *Working Paper*.

Durante, Ruben, Luigi Guiso, and Giorgio Gulino (2020). *Asocial Capital: Civic Culture and Social Distancing During Covid-19*. Working Paper. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3615583.

Engle, Samuel, John Stromme, and Anson Zhou (2020). "Staying at Home: Mobility Effects of COVID-19". In: *SSRN Working Paper*, pp. 1–16. URL: http://dx.doi.org/10.2139/ssrn.3565703.

Fearon, James D, Macartan Humphreys, and Jeremy M Weinstein (2009). "Can development aid contribute to social cohesion after civil war? Evidence from a field experiment in post-conflict Liberia". In: *American Economic Review* 99.2, pp. 287–91.

Feigenberg, Benjamin, Erica M Field, and Rohini Pande (2010). "Building social capital through microfinance". In: *NBER Working Paper Series* 16018.

Fowler, James H. (2006). "Altruism and Turnout". In: *The Journal of Politics* 68.3, pp. 674–683.

Fowler, James H. and Cindy D. Kam (2007). "Beyond the Self: Social Identity, Altruism, and Political Participation". In: *The Journal of Politics* 69.3, pp. 813–827.

Franzen, Axel and Katrin Botzen (2011). "Vereine in Deutschland und ihr Beitrag zum Wohlstand der Regionen". In: *Soziale Welt*, pp. 391–413.

Frey, Carl Benedikt, Chinchih Chen, and Giorgio Presidente (2020). "Democracy, Culture, and Contagion: Political Regimes and Countries Responsiveness to Covid-19". In: *Covid Economics* 18, pp. 1–20.

Friedson, Andrew I., Drew McNichols, Joseph J. Sabia, and Dhaval Dave (2020). "Did California's Shelter-in-Place Order Work? Early Coronavirus-related Public Health Effects". In: *NBER Working Paper Series* 26992, pp. 1–88.

Giuliano, Paola and Romain Wacziarg (2020). "Who Voted for Trump? Populism and Social Capital". In: *National Bureau of Economic Research Working Paper*.

Glaeser, Edward L., Bruce Sacerdote, and Jose A. Scheinkman (1996). "Crime and Social Interactions". In: *The Quarterly Journal of Economics* 111.2, pp. 507–548.

Glogowsky, Ulrich, Emanuel Hansen, and Simeon Schächtele (2020). "How Effective Are Social Distancing Policies? Evidence on the Fight Against COVID-19 from Germany". In: *CESifo Working Paper No. 8361*.

Goldin, Claudia and Lawrence F. Katz (1999). “Human Capital and Social Capital: The Rise of Secondary Schooling in America, 1910–1940”. In: *Journal of Interdisciplinary History* 29.4, pp. 683–723.

Goodman-Bacon, Andrew and Jan Marcus (2020). “Using Difference-in-Differences to Identify Causal Effects of Covid-19 Policies”. In: *Survey Research Methods* 14.2, pp. 153–158.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2004). “The Role of Social Capital in Financial Development”. In: *American Economic Review* 94.3, pp. 526–556.

— (2011). “Civic Capital As the Missing Link”. In: *Handbook of Social Economics*. Vol. 1. Elsevier, pp. 417–480.

Heide, Matthias an der and Osamah Hamouda (2020). “Schätzung der aktuellen Entwicklung der SARS-Cov-2-Epidemie in Deutschland”. In: *Epidemiologisches Bulletin* 17, pp. 10–16.

Jankowski, Richard (2007). “Altruism and the Decision to Vote: Explaining and Testing High Voter Turnout”. In: *Rationality and Society* 19.1, pp. 5–34.

Jung, Minsoo, Leesa Lin, and Kasisomayajula Viswanath (2013). “Associations between health communication behaviors, neighborhood social capital, vaccine knowledge, and parents’ H1N1 vaccination of their children”. In: *Vaccine* 31.42, pp. 4860–4866.

Knack, Stephen and Philip Keefer (1997). “Does Social Capital Have an Economic Payoff? A Cross-Country Investigation”. In: *Quarterly Journal of Economics* 112.4, pp. 1251–1288.

Lauer, Stephen A. et al. (2020). “The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application”. In: *Annals of Internal Medicine* 172.9, pp. 577–582. DOI: 10.7326/M20-0504. eprint: https://www.acpjournals.org/doi/pdf/10.7326/M20-0504. URL: https://www.acpjournals.org/doi/abs/10.7326/M20-0504.

Lichter, Andreas, Max Löffler, and Sebastian Siegloch (2020). “The Long-Term Costs of Government Surveillance: Insights from Stasi Spying in East Germany”. In: *Journal of the European Economic Association*.

Nannicini, Tommaso, Andrea Stella, Guido Tabellini, and Ugo Troiano (2013). “Social Capital and Political Accountability”. In: *American Economic Journal: Economic Policy* 5.2, pp. 222–50.

Oster, Emily (2019). “Unobservable selection and coefficient stability: Theory and evidence”. In: *Journal of Business & Economic Statistics* 37.2, pp. 187–204.

Ostrom, Elinor (1991). *Managing the Commons: The Evolution of Institutions for Collective Action*. New York: Cambridge University Press.

— (1999). “Social Capital: A Multifaceted Perspective”. In: ed. by I. Serageldin P. Dasgupta. Washington, DC: World Bank. Chap. Social Capital: A Fad or a Fundamental Concept, pp. 172–214.

Painter, Marcus O. and Tian Qiu (2020). “Political Beliefs Affect Compliance with COVID-19 Social Distancing Orders”. In: *SSRN Working Paper*, pp. 1–21. URL: `http://dx.doi.org/10.2139/ssrn.3569098`.

Putnam, Robert D. (1993). *Making Democracy Work: Civic Traditions in Modern Italy*. Princeton University Press, Princeton, NJ.

— (2000). *Bowling Alone: The Collapse and Revival of American Community*. Simon and Schuster.

Rönnerstrand, Björn (2014). “Social capital and immunization against the 2009 A(H1N1) pandemic in the American States”. In: *Public Health* 128.8, pp. 709–715.

Satyanath, Shanker, Nico Voigtländer, and Hans-Joachim Voth (2017). “Bowling for Fascism: Social Capital and the Rise of the Nazi Party”. In: *Journal of Political Economy* 125.2, pp. 478–526.

Tabellini, Guido (2008). “The Scope of Cooperation: Norms and Incentives”. In: *Quarterly Journal of Economics* 123.3, pp. 905–950.

— (2010). “Culture and Institutions: Economic Development in the Regions of Europe”. In: *Journal of the European Economic Association* 8.4, pp. 677–716.

Van Bavel, Jay J. et al. (2020). “Using Social and Behavioural Science to Support Covid-19 Pandemic Response”. In: *Nature Human Behaviour*, pp. 1–12.

Xue, Xindong, W. Robert Reed, and Andrea Menclova (2020). “Social capital and health: A meta-analysis”. In: *Journal of Health Economics* 72, p. 102317. ISSN: 0167-6296. DOI: `https://doi.org/10.1016/j.jhealeco.2020.102317`. URL: `http://www.sciencedirect.com/science/article/pii/S0167629619300141`.

Yang, Xiaobo et al. (2020). “Clinical Course and Outcomes of Critically Ill Patients with Sars-Cov-2 Pneumonia in Wuhan, China: A Single-centered, Retrospective, Observational Study”. In: *The Lancet Respiratory Medicine* 8.5, pp. 475–481. ISSN: 2213-

2600. DOI: https://doi.org/10.1016/S2213-2600(20)30079-5. URL: http://www.sciencedirect.com/science/article/pii/S2213260020300795.

A Online Appendix: Data

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 district-day level. The numbers have been published daily since March 11^{th}. The four districts in the state of Vorarlberg start reporting cases on March 16^{th} (results do not change when we drop them). We impute occasionally missing daily observations by linear interpolation. We normalize this variable with population numbers from Statistics Austria.	Federal Ministry of Social Affairs, Health, Care and Consumer Protection; Addendum (Austrian Newspaper) for values from March 11^{th} to 22^{nd}; 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 May 2020 minus the average number of deaths on the same month in the period from 2015 to 2019 at the Lower Tier Local Authority-month 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 & National Records of Scotland
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^{st} to May 31^{th} 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. The data are available for 7,357 out of the 7,904 municipalities covering about 93% of all municipalities or 95% of the total population.	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 May 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 county-day level. 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	2018 - 2020	The number of deaths recorded from January 1^{st} to May 31^{th} 2020 minus the average number of deaths in the period from 2018 to 2019 at the municipality-block level. Each month is divided in three blocks: from the 1^{st} to the 10^{th}, from the 11^{th} to the 21^{th}, and the remaining days. Since the public data set censors observations with five or less deaths, we obtained the non-censored data. We normalize this variable with population numbers from Statistics Sweden.	Statistics Sweden
Switzerland: cumulative Covid-19 cases per 100,000 inhabitants	2020	The total number of Covid-19 infections at the canton-day level. We impute occasionally missing daily observations by linear interpolation. We normalize this variable with population numbers from the Swiss Federal Statistical Office.	Health Offices of the Swiss Cantons; 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 district level.	Austrian State Governments
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)

continued

Table A.1 continued

	year	description	source
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
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 county level.	Swedish Election Authority
Switzerland: turnout	2019	Turnout to the 2019 national parliament election held in October 2019 at the canton level.	Swiss Federal Statistical Office
Switzerland: registered organ donors per capita	2020	Number of registered organ donors willing to donate as of June 2020, relative to population at the canton level.	Swisstransplant
Panel C − Control Variables			
Austria: hospital beds per 1,000 inhabitants	2019	The number of hospital beds at the district level normalized with population numbers from Statistics Austria.	Federal Ministry of Social Affairs, Health, Care and Consumer Protection
Austria: share educated	2017	The share of the population at the district level that has completed at least *Matura*.	Statistics Austria
Austria: share white-collar	2017	The share of working population at the district 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 NUTS3 level.	Statistics Austria
Austria: share old	2017	The share of the population at the district level that is older than 65 years of age.	Statistics Austria
Austria: population density	2019	The number of inhabitants per square kilometer at the district 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 *Abitur*.	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 NUTS2 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

continued

Table A.1 continued

	year	description	source
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
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: hospital beds per 1,000 inhabitants	2019	The number of hospital beds at the county level normalized with population numbers from Statistics Sweden.	Swedish Association of Local Authorities and Regions
Sweden: share educated	2019	The share of the population at the county level that has at least a college degree.	Statistics Sweden
Sweden: share white-collar	2019	The share of working population at the county level that is employed in a white-collar sector.	OECD
Sweden: GPD per capita	2017	Gross domestic product per inhabitant at current prices converted into Euros at the county level.	OECD
Sweden: share old	2019	The share of the population at the county (municipality) level that is older than 65 years of age.	Statistics Sweden
Sweden: population density	2019	The number of inhabitants per square kilometer at the county (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: hospital beds per 1,000 inhabitants	2019	The number of hospital beds at the canton level normalized with population data from the Swiss Federal Statistical Office.	Swiss Federal Statistical Office
Switzerland: share educated	2017	The share of the population at the canton level that has completed at least high-school.	OECD
Switzerland: share white-collar	2018	The share of working population at the canton level that is employed in a white-collar sector.	Swiss Federal Statistical Office
Switzerland: GPD per capita	2017	Gross domestic product per inhabitant at current prices converted into Euros at the canton level.	OECD
Switzerland: share old	2019	The share of the population at the canton 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 canton 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: district level							
turnout	0.59	0.52	0.66	0.08	0.43	0.71	94
population (in 100,000)	0.94	0.44	0.99	1.93	0.02	18.97	94
population density (in 1000/km^2)	0.28	0.05	0.14	0.63	0.02	4.49	94
GDP per capita (in 1,000€)	37.55	29.60	46.10	8.94	23.00	54.50	94
hospital beds per 1,000 inhabitants	6.74	2.19	9.48	6.56	0.00	29.04	94
share white-collar	0.09	0.08	0.11	0.03	0.05	0.19	94
share old	0.24	0.18	0.22	0.02	0.16	0.25	94
share educated	0.63	0.61	0.66	0.04	0.52	0.70	94
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 1000/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

continued

Table A.2 continued

	mean	p25	p75	sd	min	max	N
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 1000/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
population (in 100,000)	5.64	2.35	6.22	6.17	0.84	43.42	107
population density (in 1000/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 1000/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: county level							
turnout	0.54	0.52	0.55	0.03	0.50	0.59	21
population (in 100,000)	4.92	2.45	3.64	5.73	0.60	23.77	21
population density (in 1000/km^2)	0.05	0.02	0.05	0.08	0.00	0.36	21
GDP per capita (in 1,000€)	40.56	37.23	41.14	6.07	33.54	61.32	21
hospital beds per 1,000 inhabitants	2.10	1.90	2.29	0.30	1.41	2.58	21
share white-collar	0.49	0.47	0.52	0.04	0.43	0.59	21
share old	0.22	0.21	0.24	0.02	0.16	0.25	21
share educated	0.36	0.35	0.39	0.09	0.02	0.55	21
Switzerland: canton level							
turnout	0.41	0.38	0.43	0.06	0.32	0.63	26
organ donors per capita	0.01	0.01	0.01	0.00	0.01	0.02	26
population (in 100,000)	3.29	0.73	4.10	3.52	0.16	15.21	26
population density (in 1000/km^2)	0.50	0.09	0.35	1.04	0.03	5.26	26
GDP per capita (in 1,000€)	48.09	33.27	51.17	21.79	25.33	111.17	26
hospital beds per 1,000 inhabitants	2.45	1.73	1.02	1.00	1.11	6.16	26
share white-collar	0.70	0.65	0.74	0.08	0.57	0.86	26
share old	0.19	0.18	0.20	0.02	0.16	0.23	26
share educated	0.47	0.43	0.51	0.07	0.29	0.59	26
Italy: municipality level							
turnout	0.59	0.48	0.71	0.15	0.12	1.00	7357
population (in 100,000)	0.08	0.01	0.06	0.44	0.00	28.56	7357
population density (in 1000/km^2)	0.31	0.04	0.29	0.66	0.00	12.22	7357
taxable income per capita (in 1,000€)	12.70	9.85	15.06	3.31	3.04	35.45	7357
hospitals per 100,000 inhabitants	0.83	0.00	0.00	5.54	0.00	235.85	7357
share old	0.29	0.25	0.33	0.06	0.09	0.69	7357
share educated	0.07	0.05	0.09	0.03	0.00	0.27	7357
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 1000/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

continued

Table A.2 continued

	mean	p25	p75	sd	min	max	N
share educated	0.78	0.76	0.81	0.04	0.68	0.87	290

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

country	**area name**	**# areas**	**NUTS1 name**	**# NUTS1**
Austria	District (*Bezirk*)	94	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	County (*Län*)	21	Land (*Landsdelar*)	3
Switzerland	Canton (*Kanton*)	26	group of Cantons (*Kanton*)	7

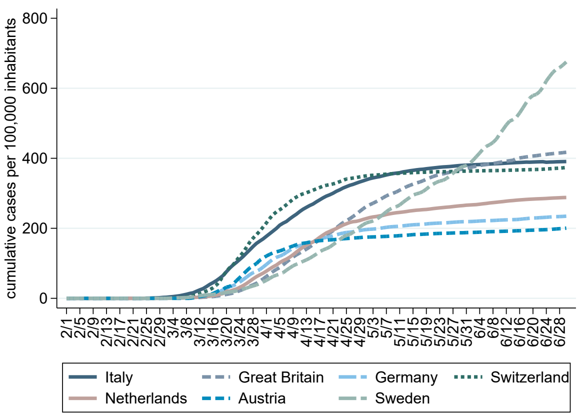
Notes: This table provides an overview about the different geographical units within each country. With the exception of Austria, the Netherlands and Great Britain, all "areas" correspond to the NUTS3 regions. The column NUTS1 refers to the name of the NUTS1 region, except for Switzerland where the NUTS1 region corresponds to the whole country. Hence, we are using the NUTS2 region for Switzerland.

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

country	**first case**	**ban of gatherings**	**school closure**	**lockdown**
Italy	Jan. 31^{th}	Feb. 23^{th}	Mar. 4^{th}	Mar. 9^{th}
Austria	Feb. 25^{th}	Mar. 10^{th}	Mar. 10^{th}	Mar. 16^{th}
Germany	Jan. 28^{th}	Mar. 8^{th}	Mar. 16^{th}	Mar. 23^{nd}
Netherlands	Feb. 27^{th}	Mar. 12^{th}	Mar. 15^{th}	Mar. 23^{rd}
Sweden	Jan. 31^{st}	Mar. 11^{th}	-	-
Switzerland	Feb. 25^{th}	Feb. 28^{th}	Mar.13^{th}	Mar. 16^{th}
Great Britain	Jan. 29^{th}	Mar. 23^{rd}	Mar. 18^{th}	Mar. 23^{rd}

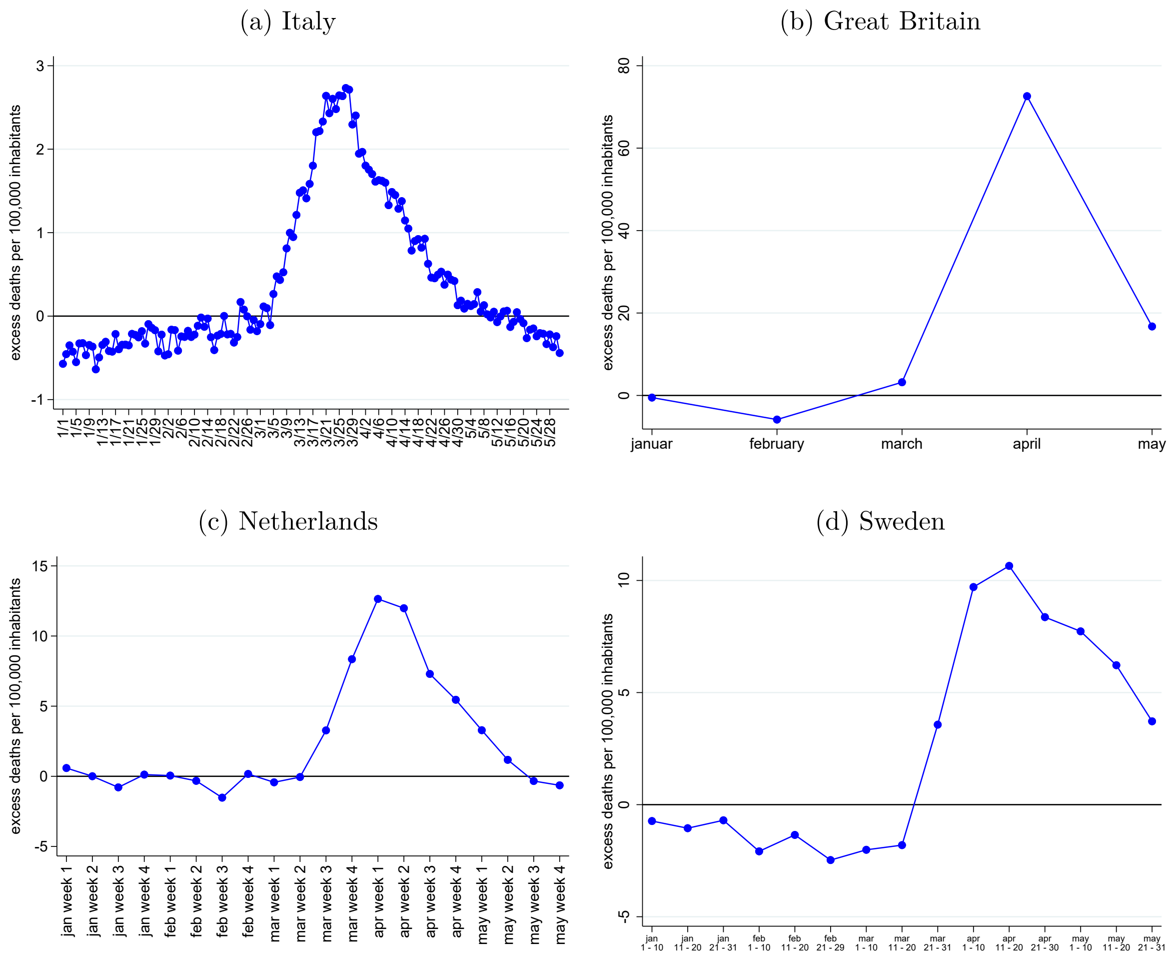
Notes: This table displays the timeline of the onset of Covid-19 in each country and the respective policy measures implemented to contain the spread.

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.

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 May 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 and for Sweden, it includes 2018 and 2019, since earlier data is not available.

B Online Appendix: Additional Results

Table B.2: 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	-0.277*** (0.052)	-0.267*** (0.050)	-0.269*** (0.051)	-0.171*** (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

continued

Table B.2 continued

	(1)		(2)		(3)		(4)	
weeks-since-outbreak x day FE	no		no		yes		yes	
controls x day FE	no		no		no		yes	
mean	4.967		4.967		4.967		4.967	
observations	40,062		40,062		39,866		39,866	
Panel C – Germany								
turnout x 30jun2020	-0.152***	(0.053)	-0.084	(0.054)	-0.100*	(0.056)	-0.116*	(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	4.725		4.725		4.722		4.722	
observations	43,393		43,393		43,268		43,268	
Panel D – Switzerland								
turnout x 30jun2020	-0.170	(0.175)	-0.173	(0.180)	-0.171	(0.208)	-0.243	(0.428)
canton FE	yes		yes		yes		yes	
NUTS2 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	5.302		5.302		5.304		5.304	
observations	2,562		2,562		2,519		2,519	
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	
Panel F – Austria								
turnout x 30jun2020	-0.185	(0.135)	-0.187	(0.135)	-0.191	(0.136)	-0.201	(0.160)
district 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	4.703		4.703		4.702		4.702	
observations	9,960		9,960		9,904		9,904	
Panel G – Sweden								
turnout x 30jun2020	-0.510**	(0.229)	-0.465*	(0.259)	-0.419	(0.259)	-0.336	(0.403)
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	4.788		4.788		4.766		4.766	
observations	2,330		2,330		2,189		2,189	

Notes: This table presents the regression results in equation (1). For the sake of brevity, we omit all coefficients, but the last one. All coefficients are available upon request. Standard errors clustered at the 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.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	

continued

Table B.3 continued

	(1)		(2)		(3)		(4)	
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 – Switzerland								
organ donors per capita x 30jun2020	-0.073	(0.098)	-0.072	(0.096)	-0.082	(0.109)	-0.241	(0.153)
canton FE	yes		yes		yes		yes	
NUTS2 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	5.302		5.302		5.304		5.304	
observations	2,562		2,562		2,519		2,519	
Panel D – Great Britain								
blood donors per capita x 30jun2020	-0.244***	(0.076)	-0.279***	(0.071)	-0.280***	(0.072)	-0.232***	(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		4.967		4.967	
observations	40,062		40,062		39,866		39,866	
Panel E – Germany								
associations per 1k inhabitants x 30jun2020	-0.115**	(0.049)	-0.126***	(0.046)	-0.126***	(0.047)	-0.105**	(0.049)
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	4.725		4.725		4.722		4.722	
observations	43,393		43,393		43,268		43,268	
Panel F – 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 and Switzerland), 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 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

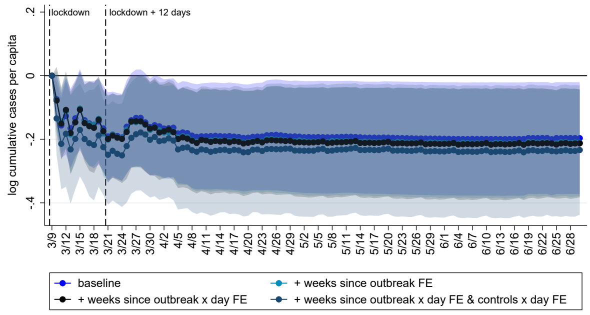
Table B.1: Selection on unobservables: Oster (2019)

	(1) uncontrolled coefficient	(2) controlled coefficient	(3) bounded coefficient
Italy	-0.340	-0.337	-0.336
	[0.008]	[0.057]	
Great Britain	-0.269	-0.171	-0.122
	[0.028]	[0.068]	
Germany	-0.097	-0.110	-0.118
	[0.024]	[0.053]	
Switzerland	-0.171	-0.243	-0.268
	[0.063]	[0.506]	
Austria	-0.195	-0.203	-0.206
	[0.026]	[0.110]	
Netherlands	-0.322	-0.270	-0.237
	[0.056]	[0.108]	
Sweden	-0.465	-0.285	-0.215
	[0.093]	[0.410]	

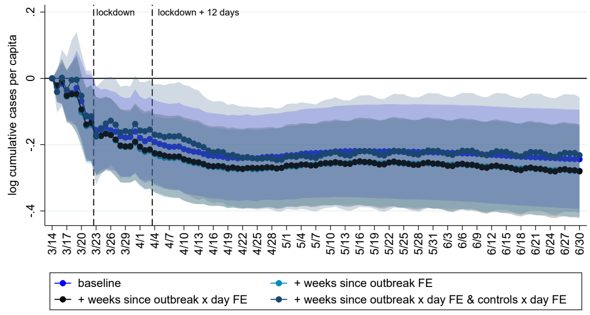
Notes: This table reports the turnout coefficients for each country at the final day of our sample. Column 1 presents our baseline results from equation (1) including the weeks since outbreak x day fixed effects. Column 2 reports the same coefficients if we include our set of controls interacted with 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 B.1: Alternative social capital measures with additional fixed effects and controls

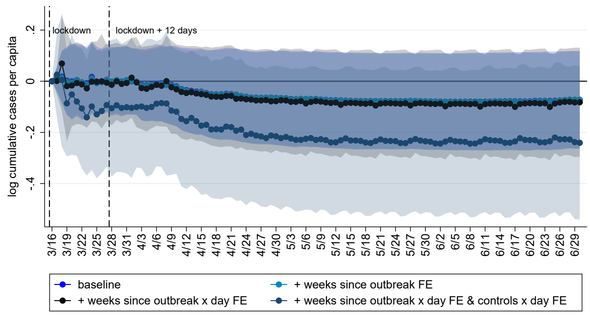
(a) Blood donations per capita, Italy



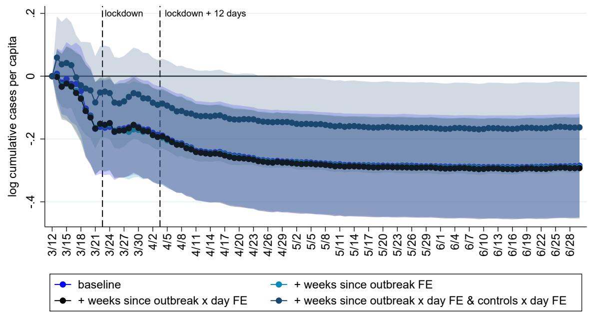
(b) Blood donations per capita, UK



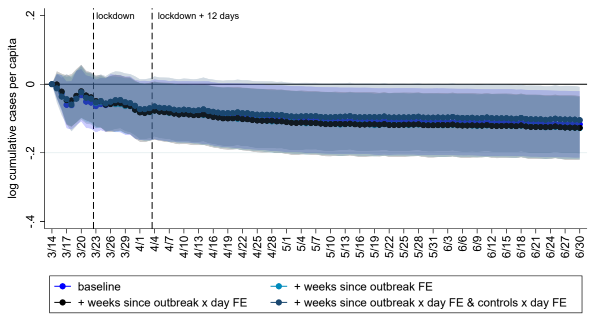
(c) Organ donors per capita, Switzerland



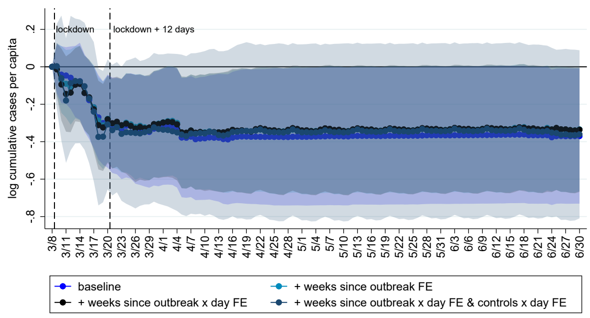
(d) Organ donors per capita, Netherlands



(e) Associations per capita, Germany



(f) 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 (1) 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 panels (c) and (d) we use the number of registered organ donors per capita as a proxy, in panel (e) we use associations per capita, in panel (f) literacy rates in 1821 (see Table B.3 for point estimates).

Table B.4: Effect of social capital on excess deaths

	(1)		(2)	
Panel A − Italy				
turnout x 01feb2020	-0.029	(0.029)	-0.029	(0.030)
turnout x 02feb2020	-0.026	(0.029)	-0.023	(0.029)
turnout x 03feb2020	-0.021	(0.028)	-0.017	(0.029)
turnout x 04feb2020	-0.021	(0.028)	-0.017	(0.028)
turnout x 05feb2020	-0.007	(0.027)	-0.003	(0.027)
turnout x 06feb2020	-0.006	(0.028)	0.001	(0.028)
turnout x 07feb2020	0.005	(0.027)	0.012	(0.028)
turnout x 08feb2020	0.035	(0.026)	0.038	(0.027)
turnout x 09feb2020	0.014	(0.026)	0.022	(0.026)
turnout x 10feb2020	0.009	(0.026)	0.012	(0.026)
turnout x 11feb2020	0.007	(0.024)	0.014	(0.025)
turnout x 12feb2020	0.018	(0.023)	0.024	(0.023)
turnout x 13feb2020	-0.012	(0.023)	-0.008	(0.023)
turnout x 14feb2020	-0.018	(0.022)	-0.013	(0.022)
turnout x 15feb2020	-0.020	(0.021)	-0.018	(0.021)
turnout x 16feb2020	-0.012	(0.021)	-0.012	(0.021)
turnout x 17feb2020	-0.027	(0.018)	-0.028	(0.019)
turnout x 18feb2020	-0.020	(0.016)	-0.019	(0.016)
turnout x 19feb2020	-0.026*	(0.014)	-0.026*	(0.014)
turnout x 21feb2020	0.008	(0.012)	0.006	(0.013)
turnout x 22feb2020	0.004	(0.016)	0.005	(0.016)
turnout x 23feb2020	-0.012	(0.018)	-0.013	(0.018)
turnout x 24feb2020	-0.007	(0.019)	-0.009	(0.019)
turnout x 25feb2020	0.001	(0.020)	-0.003	(0.020)
turnout x 26feb2020	0.013	(0.021)	0.013	(0.022)
turnout x 27feb2020	0.014	(0.023)	0.014	(0.023)
turnout x 28feb2020	-0.004	(0.023)	-0.004	(0.024)
turnout x 29feb2020	0.001	(0.024)	0.006	(0.024)
turnout x 01mar2020	0.009	(0.025)	0.009	(0.026)
turnout x 02mar2020	0.017	(0.025)	0.014	(0.026)
turnout x 03mar2020	0.018	(0.025)	0.016	(0.026)
turnout x 04mar2020	0.016	(0.025)	0.015	(0.025)
turnout x 05mar2020	0.013	(0.026)	0.011	(0.026)
turnout x 06mar2020	0.029	(0.026)	0.031	(0.026)
turnout x 07mar2020	0.026	(0.026)	0.026	(0.026)
turnout x 08mar2020	0.010	(0.027)	0.007	(0.027)
turnout x 09mar2020	0.015	(0.027)	0.013	(0.027)
turnout x 10mar2020	0.015	(0.027)	0.010	(0.027)
turnout x 11mar2020	0.022	(0.027)	0.017	(0.028)
turnout x 12mar2020	0.010	(0.028)	0.005	(0.028)
turnout x 13mar2020	-0.003	(0.028)	-0.010	(0.028)
turnout x 14mar2020	-0.004	(0.029)	-0.012	(0.029)
turnout x 15mar2020	-0.004	(0.029)	-0.013	(0.029)
turnout x 16mar2020	-0.008	(0.029)	-0.016	(0.030)
turnout x 17mar2020	-0.007	(0.030)	-0.011	(0.030)
turnout x 18mar2020	-0.007	(0.029)	-0.010	(0.029)
turnout x 19mar2020	-0.008	(0.029)	-0.013	(0.029)
turnout x 20mar2020	-0.007	(0.029)	-0.014	(0.029)
turnout x 21mar2020	-0.022	(0.030)	-0.031	(0.030)
turnout x 22mar2020	-0.037	(0.030)	-0.048	(0.031)
turnout x 23mar2020	-0.045	(0.031)	-0.055*	(0.031)
turnout x 24mar2020	-0.037	(0.030)	-0.048	(0.031)
turnout x 25mar2020	-0.043	(0.030)	-0.053*	(0.031)
turnout x 26mar2020	-0.044	(0.031)	-0.056*	(0.031)
turnout x 27mar2020	-0.036	(0.031)	-0.049	(0.031)
turnout x 28mar2020	-0.063**	(0.031)	-0.075**	(0.031)
turnout x 29mar2020	-0.055*	(0.030)	-0.070**	(0.031)
turnout x 30mar2020	-0.061*	(0.031)	-0.077**	(0.032)
turnout x 31mar2020	-0.054*	(0.031)	-0.073**	(0.031)
turnout x 01apr2020	-0.064**	(0.031)	-0.082***	(0.031)
turnout x 02apr2020	-0.049	(0.031)	-0.067**	(0.031)
turnout x 03apr2020	-0.058*	(0.031)	-0.073**	(0.031)
turnout x 04apr2020	-0.037	(0.031)	-0.055*	(0.031)
turnout x 05apr2020	-0.058*	(0.032)	-0.078**	(0.032)
turnout x 06apr2020	-0.052*	(0.031)	-0.073**	(0.032)
turnout x 07apr2020	-0.060*	(0.031)	-0.080**	(0.032)
turnout x 08apr2020	-0.052*	(0.032)	-0.074**	(0.032)
turnout x 09apr2020	-0.057*	(0.032)	-0.077**	(0.032)
turnout x 10apr2020	-0.055*	(0.032)	-0.074**	(0.032)
turnout x 11apr2020	-0.058*	(0.032)	-0.077**	(0.033)
turnout x 12apr2020	-0.067**	(0.032)	-0.088***	(0.033)
turnout x 13apr2020	-0.057*	(0.032)	-0.076**	(0.032)
turnout x 14apr2020	-0.057*	(0.032)	-0.077**	(0.032)

continued

Table B.4 continued

	(1)		(2)	
turnout x 15apr2020	-0.049	(0.032)	-0.068**	(0.032)
turnout x 16apr2020	-0.060*	(0.032)	-0.080**	(0.032)
turnout x 17apr2020	-0.059*	(0.032)	-0.080**	(0.032)
turnout x 18apr2020	-0.062*	(0.032)	-0.080**	(0.032)
turnout x 19apr2020	-0.052	(0.032)	-0.071**	(0.032)
turnout x 20apr2020	-0.052	(0.032)	-0.070**	(0.032)
turnout x 21apr2020	-0.058*	(0.032)	-0.076**	(0.032)
turnout x 22apr2020	-0.058*	(0.032)	-0.078**	(0.032)
turnout x 23apr2020	-0.064**	(0.032)	-0.083**	(0.033)
turnout x 24apr2020	-0.060*	(0.032)	-0.079**	(0.032)
turnout x 25apr2020	-0.055*	(0.032)	-0.075**	(0.032)
turnout x 26apr2020	-0.074**	(0.032)	-0.094***	(0.032)
turnout x 27apr2020	-0.068**	(0.032)	-0.089***	(0.032)
turnout x 28apr2020	-0.071**	(0.032)	-0.090***	(0.032)
turnout x 29apr2020	-0.076**	(0.033)	-0.095***	(0.033)
turnout x 30apr2020	-0.074**	(0.032)	-0.093***	(0.032)
turnout x 01may2020	-0.075**	(0.033)	-0.099***	(0.033)
turnout x 02may2020	-0.087***	(0.033)	-0.110***	(0.033)
turnout x 03may2020	-0.095***	(0.033)	-0.116***	(0.034)
turnout x 04may2020	-0.091***	(0.033)	-0.112***	(0.033)
turnout x 05may2020	-0.091***	(0.033)	-0.112***	(0.033)
turnout x 06may2020	-0.088***	(0.033)	-0.109***	(0.033)
turnout x 07may2020	-0.086***	(0.033)	-0.107***	(0.033)
turnout x 08may2020	-0.084**	(0.033)	-0.103***	(0.033)
turnout x 09may2020	-0.086***	(0.033)	-0.106***	(0.033)
turnout x 10may2020	-0.086***	(0.033)	-0.107***	(0.033)
turnout x 11may2020	-0.081**	(0.033)	-0.102***	(0.033)
turnout x 12may2020	-0.092***	(0.033)	-0.110***	(0.033)
turnout x 13may2020	-0.089***	(0.033)	-0.110***	(0.033)
turnout x 14may2020	-0.074**	(0.033)	-0.097***	(0.033)
turnout x 15may2020	-0.084**	(0.034)	-0.105***	(0.033)
turnout x 16may2020	-0.091***	(0.034)	-0.110***	(0.034)
turnout x 17may2020	-0.087***	(0.033)	-0.107***	(0.033)
turnout x 18may2020	-0.081**	(0.033)	-0.100***	(0.034)
turnout x 19may2020	-0.075**	(0.033)	-0.094***	(0.033)
turnout x 20may2020	-0.068**	(0.033)	-0.090***	(0.033)
turnout x 21may2020	-0.072**	(0.033)	-0.092***	(0.033)
turnout x 22may2020	-0.062*	(0.033)	-0.084**	(0.033)
turnout x 23may2020	-0.063*	(0.034)	-0.085**	(0.034)
turnout x 24may2020	-0.060*	(0.034)	-0.083**	(0.034)
turnout x 25may2020	-0.065*	(0.033)	-0.087**	(0.034)
turnout x 26may2020	-0.064*	(0.033)	-0.086***	(0.033)
turnout x 27may2020	-0.072**	(0.033)	-0.094***	(0.033)
turnout x 28may2020	-0.068**	(0.033)	-0.090***	(0.033)
turnout x 29may2020	-0.069**	(0.033)	-0.090***	(0.034)
turnout x 30may2020	-0.075**	(0.034)	-0.098***	(0.034)
turnout x 31may2020	-0.073**	(0.034)	-0.095***	(0.034)
municipality FE	yes		yes	
NUTS3 x day FE	yes		yes	
controls x day FE	no		yes	
mean	1.008		1.008	
observations	440,485		440,485	
Panel B − Netherlands				
turnout x feb week 1	-0.007	(0.071)	-0.064	(0.088)
turnout x feb week 2	-0.051	(0.074)	-0.081	(0.095)
turnout x feb week 4	0.014	(0.067)	0.045	(0.088)
turnout x mar week 1	-0.006	(0.105)	-0.017	(0.150)
turnout x mar week 2	0.103	(0.102)	-0.085	(0.136)
turnout x mar week 3	-0.010	(0.103)	-0.130	(0.122)
turnout x mar week 4	-0.037	(0.098)	-0.070	(0.126)
turnout x apr week 1	-0.095	(0.092)	-0.140	(0.120)
turnout x apr week 2	-0.079	(0.090)	-0.113	(0.111)
turnout x apr week 3	-0.159*	(0.087)	-0.215**	(0.107)
turnout x apr week 4	-0.102	(0.087)	-0.108	(0.105)
turnout x may week 1	-0.115	(0.089)	-0.143	(0.107)
turnout x may week 2	-0.179*	(0.091)	-0.156	(0.113)
turnout x may week 3	-0.155*	(0.091)	-0.130	(0.115)
turnout x may week 4	-0.142	(0.091)	-0.137	(0.108)
municipality FE	yes		yes	
NUTS3 x week FE	yes		yes	
controls x week FE	no		yes	
mean	3.466		3.466	
observations	3,618		3,618	
Panel C − Great Britain				

continued

Table B.4 continued

	(1)		(2)	
turnout x march	-0.009	(0.180)	-0.083	(0.248)
turnout x april	-0.178	(0.135)	-0.353*	(0.210)
turnout x may	-0.172	(0.136)	-0.340	(0.210)
lower tier local authority FE	yes		yes	
NUTS1 x month FE	yes		yes	
controls x month FE	no		yes	
mean	3.530		3.530	
observations	977		977	
Panel D – Sweden				
turnout x feb 1^{st} - 10^{th}	-0.063	(0.147)	-0.015	(0.237)
turnout x feb 11^{th} - 20^{th}	-0.018	(0.136)	-0.084	(0.230)
turnout x feb 21^{th} - 29^{th}	-0.168	(0.145)	-0.221	(0.249)
turnout x mar 1^{st} - 10^{th}	-0.107	(0.140)	-0.096	(0.259)
turnout x mar 11^{th} - 20^{th}	-0.133	(0.139)	-0.034	(0.201)
turnout x apr 1^{st} - 10^{th}	-0.173*	(0.093)	-0.299*	(0.168)
turnout x apr 11^{th} - 20^{th}	-0.240**	(0.095)	-0.524**	(0.207)
turnout x apr 21^{th} - 30^{th}	-0.166*	(0.092)	-0.378*	(0.200)
turnout x may 1^{st} - 10^{th}	-0.194**	(0.091)	-0.396**	(0.188)
turnout x may 11^{th} - 20^{th}	-0.132	(0.096)	-0.365**	(0.183)
turnout x may 21^{th} - 31^{th}	-0.125	(0.095)	-0.349*	(0.189)
municipality FE	yes		yes	
NUTS3 x block FE	yes		yes	
controls x block FE	no		yes	
mean	3.256		3.256	
observations	1,560		1,560	

Notes: This table presents the regression results from our excess mortality regression for Italy, Great Britain, Sweden and the Netherlands in equation (1). 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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$