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DP14866
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Alina Bartscher - alina.bartscher@uni-bonn.de
University of Bonn

Sebastian Seitz - sseitz@mail.uni-mannheim.de
University of Mannheim and ZEW

Sebastian Siegloch - siegloch@uni-mannheim.de
University of Mannheim, ZEW Mannheim and CEPR

Michaela Slotwinski - michaela.slotwinski@unibas.ch
University of Basel and ZEW

Nils Wehrhöfer - nils.wehrhoefer@gess.uni-mannheim.de
University of Mannheim and ZEW

Social capital and the spread of Covid-19:
Insights from European countries

Alina Kristin Bartscher[*]   Sebastian Seitz[†]   Sebastian Siegloch[‡]

Michaela Slotwinski[§]   Nils Wehrhöfer[¶‖]

First version: May 2020

This version: July 2021

Abstract

We investigate the effect of social capital on health outcomes during the Covid-19 pandemic in independent analyses for Austria, Germany, Great Britain, Italy, the Netherlands, Sweden and Switzerland. Exploiting detailed geographical variation within countries, we show that a one-standard-deviation increase in social capital leads to between 14% and 34% fewer Covid-19 cases per capita accumulated from mid-March until end of June 2020, as well as between 6% and 35% fewer excess deaths per capita. Our results highlight the positive health returns of strengthening social capital.

JEL codes: D04, A13, D91, H11, H12, I10, I18, Z1

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

[*] University of Bonn, Adenauerallee 24-42, 53113 Bonn, Germany, alina.bartscher@uni-bonn.de

[†] ZEW and University of Mannheim, L7 3-5, 68131 Mannheim, Germany, sebastian.seitz@gess.uni-mannheim.de

[‡] ZEW and University of Mannheim, L7 3-5, 68131 Mannheim, Germany, sebastian.siegloch@zew.de

[§] ZEW and University of Basel, Peter Merian-Weg 6, 4002 Basel, Switzerland, michaela.slotwinski@unibas.ch

[¶] ZEW and University of Mannheim, L7 3-5, 68131 Mannheim, Germany, nils.wehrhoefer@gess.uni-mannheim.de.

1   Introduction

The Covid-19 pandemic has triggered a large amount of research contributing to a better understanding of the virus, its containment and individuals' behavior in a pandemic. When medical answers like pharmaceuticals or vaccines are not (yet) widely available, human behavior is the key margin to contain a pandemic (Van Bavel et al., 2020).[1] Hence, it is not surprising that policymakers and health experts around the world have appealed to the social responsibility of their citizens, asking them to limit social contacts and follow strict hygiene and distancing recommendations.[2] Put differently, politicians urged their citizens to consider the social costs of their individual actions. We define this willingness to act collectively and pursue socially valuable activities as social capital (Putnam, 1993, 2000). In this definition, sometimes also called 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 Covid-19 crisis. In this, we primarily relate to what is called the "bridging" dimension of social capital (Putnam, 2000; Schmitt and Eijk, 2007) that stresses across-group solidarity.

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. To the best of our knowledge, this study is the first to systematically analyze the dynamic relationship between social capital and health outcomes, as measured by Covid-19 cases and excess mortality.[3] More explicitly, we provide evidence from independent analyses for seven European countries – Austria, Germany, Great Britain, Italy, the Netherlands, Sweden and Switzerland.[4] We show that social capital has a causal and positive effect on pandemic-related health outcomes separately for each individual country. We contribute to the literature by presenting robust evidence at the fine-grained geographical level of micro-areas within countries: our analysis is at the NUTS-3 or even municipal level for some countries, as explained below. This enables us to control for confounding shocks, say regional policies implemented at the state level, by including the respective fixed effects.

We follow a well-established literature and apply various common measures of social cap-

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[1] Even after vaccines become available, people's willingness to get vaccinated likely depends on their civic norms and sense of responsibility (Chuang et al., 2015; Jung et al., 2013; Schmelz and Bowles, 2021).

[2] Two prominent examples are: 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."

[3] There are various studies that analyze the effect of social capital on individual behavior – mostly mobility (see below for a detailed discussion of the literature). However, looking at specific behavioral responses only gives a partial picture of the role of social capital in the pandemic and its net health effects, as different behavioral channels might be substitutes. For instance, individuals who restrict mobility might follow hygiene or social distancing recommendations less strictly.

[4] We selected these countries because high-frequency information on Covid-19 cases was available at a fine geographical level when writing this study in the first wave of the pandemic in early 2020.

ital. The underlying principle for the selection of our measures is that they should be official, recent and comprehensive. First, we use electoral turnout in the 2019 European election. Turnout as a proxy for social capital derives directly from the seminal contributions by Putnam (1993, 2000) and has widely been used (see, e.g. Barrios et al., 2021; Bolsen et al., 2014; Guiso et al., 2004). Turnout has three major advantages in the context of our study. First, it is comparable because it refers to the same election in six of the seven countries under study.[5] Second, turnout exhibits sufficient regional variation within countries. Third, turnout is a precise measure even at very disaggregated geographical levels. It is based on the universe of eligible voters and thus less prone to measurement and small sample problems than survey-based measures (Bauernschuster et al., 2014). As a second measure, we use blood and organ donations, which are available at sufficiently fine geographical levels and have little measurement error. Again, this is a standard proxy in the literature (Guiso et al., 2004; Putnam, 2000). Third, we use other common measures like association density (Giuliano and Wacziarg, 2020; Satyanath et al., 2017) or historical literacy rates (Tabellini, 2010) whenever available.

We choose the number of Covid-19 cases as our main outcome variable because it is a comprehensive measure of the extent of the pandemic which is available on a daily basis at fine geographical levels 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 excess mortality as an alternative outcome wherever available at fine geographical levels. Excess mortality is defined as the number of all deaths in a given time period relative to the average number for the same period in 2015-2019. In addition, we can test whether there were significant changes in micro-area-level excess deaths related to social capital (but unrelated to the new virus) before the outbreak of the pandemic.

As countries differ in many macroeconomic and Covid-19-specific aspects, it is challenging to identify the systematic effect of economic or cultural factors from cross-country comparisons (Goodman-Bacon and Marcus, 2020). For this reason, we implement a within-country-across-countries research design. We investigate the dynamic relationship between social capital and the spread of Covid-19 in independent analyses for seven European countries, implementing the identical empirical strategy in each country. We regress log cumulative cases or excess mortality on a measure of pre-determined social capital interacted with day fixed effects. This allows us to test whether the evolution of the pandemic has differed systematically depending on the level of social capital.[6] The specification boils down to a two-way fixed effects model with micro-area fixed effects and region-specific time fixed effects capturing regional outbreak patterns and policy responses. In a robustness check, we further account for potentially different outbreak

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[5] For Switzerland, we use participation in the 2019 national elections.

[6] The logarithmic model accounts for the exponential growth of infections and helps to difference out potential measurement error (Goodman-Bacon and Marcus, 2020).

patterns over time by including weeks-since-outbreak-by-day fixed effects.

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 connected, both economically and socially (see, e.g., 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 is still 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 be (voluntarily) adopted in high-social-capital areas, 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 sanction, making non-compliance more costly. Consequently, we expect containment to depend less on social capital during stricter policy regimes.

We derive the following main findings. First, high-social-capital areas accumulated between 14% and 34% fewer Covid-19 cases between mid-March and late June 2020. Likewise, high-social-capital areas recorded between 6% and 35% fewer excess deaths in Great Britain, the Netherlands, Italy, and Sweden. According to our estimates, a one-standard-deviation increase in social capital could have prevented between 1,632 deaths in Sweden and 14,303 deaths in Great Britain over the considered time period. Second, we find qualitatively similar patterns across all independently analyzed countries, which we regard as strong evidence for the robustness of our results. Third, we show a consistent dynamic pattern: the number of Covid-19 cases is initially higher in high-social-capital areas. 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 when national lockdowns are enforced. Last, our results are robust to (i) using alternative measures of social capital, (ii) adding finer fixed effects, (iii) controlling for obvious potential confounders such as income, population density, age structure, education levels or hospital density, (iv) the influence of unobserved confounders as measured by the test of Oster (2019).

To the best of our knowledge, this is the first and most comprehensive paper to empirically study the direct relationship between social capital and health outcomes during the Covid-19 pandemic. A related paper by Borgonovi, Andrieu, and Subramanian (2020) provides evidence that U.S. counties with higher social capital experienced lower case fatality rates and took less time until an area reached 10 (or 15) cases.

There is a related strand of the literature studying the relationship between social capital and individual mobility, as measured by cellphone or Google mobility data. Reducing mobility is one type of socially responsible behavior known to reduce the number of infections. Several studies show that citizens in counties with high social capital reduce mobility more than those in low-social-capital U.S. counties (Bai et al., 2020; Borgonovi and Andrieu, 2020; Brodeur et al., forthcoming; Ding et al., 2020) and/or European regions (Bargain and Aminjonov, 2020; Barrios et al., 2021; Durante et al., 2021).

These findings nicely illustrate an important mechanism driving our results. The studies show that mobility behavior, one frequently-discussed determinant of the spread of the virus, varies with social capital. By studying health outcomes, we are able to directly assess the net effect of all potential behavioral responses, including mobility. Looking at the direct net effect on cases or deaths is key to understanding the role of social capital in slowing down the pandemic. In contrast, it is very challenging to infer this net health effect by studying only one specific behavior, as it is unlikely that the different behavioral channels are perfectly positively correlated. In fact, they might even be substitutes: a socially responsible person who has to make a business trip will be more likely to wear a mask and wash her hands frequently. An alternative approach to quantify the importance of certain behaviors on health outcomes would be the use of structural models. However, one would need to model all relevant mechanisms and their interactions and find relevant data moments to meaningfully calibrate or estimate such a model, which is demanding.

Our findings demonstrate that socially responsible behavior is particularly important in the absence of containment policies or when soft containment policies like hygiene or stay-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). From this perspective, our study is also related to a literature analyzing the effects of different Covid-19 containment policies (see, e.g., Engle et al., 2020; Friedson et al., 2020; Glogowsky et al., 2020; Painter and Qiu, forthcoming).

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).

Finally, our paper complements the large literature on social capital and health. In terms of theoretical mechanisms, previous studies have established a positive link between social capital and health at the individual level – either through a reduction in stress (Folland, 2008) or via positive peer effects on health-related preferences (Costa-Font and Mladovsky,

2008). In a recent meta analysis, Xue et al. (2020) summarize the empirical literature studying the effect of social capital on health outcomes and conclude that social capital has only small positive effects. However, the previous literature has mostly focused on non-communicable diseases like cancer, heart disease or diabetes. We suggest a new channel based on collective action for the case of a highly contagious virus. In such a setting, we argue that the spread of the virus is determined by the local level of social capital and show empirically that higher levels of social capital have large mitigating effects on the spread of the disease. Our pandemic-specific estimates are substantially higher than previous empirical results on the effect of social capital in the case of non-contagious diseases. This supports the hypothesis that the positive health benefits from social capital are larger in response to contagious diseases, when behavioral adaptations matter most.

In the light of future similar health crises, our findings have important implications for policymakers. For instance, targeted communication and health education campaigns may be particularly fruitful in areas with lower social capital. Moreover, given findings from the medical literature indicating 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 vaccines become widely available, such that supply constraints are no longer binding and demand-side factors gain importance.

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 Appendix Table A.1.

2.1 Variables and Sources

We assemble data on health outcomes and social capital from seven European countries – Austria, Germany, Great Britain, Italy, the Netherlands, Sweden and Switzerland – for which the number of total Covid-19 infections is available at a sufficiently high frequency and fine geographical level for the first wave of the pandemic. We select official, recent and comprehensive statistics on both health outcomes and social capital measures.

Outcomes. Our main outcome variable is the log cumulative number of cases per 100,000 inhabitants. This measure is officially reported for fine geographical units and at a high frequency in all countries under study since the onset of the pandemic. Furthermore, cases are a comprehensive measure of the extent of the spread of the virus: every positive case can lead to further infections, increase the (health) costs for society, block hospital capacities and lead to further health complications.

For all countries, we aim at obtaining the daily number of Covid-19 cases since the early phase of the outbreak at the lowest available geographical level. For the Netherlands, Austria, Switzerland and Sweden, we were able to obtain data at the municipal level. In the other three countries, the geographical level is the NUTS-3 region.[7]

Hence, our empirical analyses are at the NUTS-3 level or below. Independent of the country-specific name, we call the geographical level at which we run our analyses "micro-area" throughout the paper.[8] We summarize the different levels of geography in Appendix Table A.3. The respective country samples start when more than 90% of all NUTS-3 areas have registered at least one official case. Such a restriction is necessary from an econometric perspective, as we can only assess the dynamics of the pandemic and their relation to social capital when a large enough share of areas within a region has been hit by the virus.[9] We later validate that our estimates are not sensitive to this particular threshold (see Appendix Figure C.4). Appendix Figure A.1 presents the evolution of cumulative Covid-19 cases per 100,000 inhabitants at the national level across countries.

A potential caveat of using cases as an outcome is that countries have measured and reported cases in different ways, for instance because they had different testing policies. Our within-country design takes care of this issue, as long as testing and measurement do not vary systematically with social capital within countries at the micro-area level. Potential differences in testing at the level of the NUTS-1-region are captured by our fixed effects (see Section 3.2).

Moreover, we use the number of excess deaths as our second health measure. Excess deaths do not suffer from potentially endogenous testing. However, high-frequency information on this measure is only available for Great Britain, the Netherlands, Italy and Sweden at

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[7] We use weekly data for Austria and Sweden, since that allows us to exploit fine-grained variation at the municipality level. In an earlier version of the paper, we used daily district-level data for Austria and daily county-level data for Sweden. The Swedish data are censored for municipalities with less than 15 cumulative cases. We impute the missing data, assuming a log-linear functional form. The results using the new data are qualitatively similar to our previous results at a higher geographical level, but much more precisely estimated.

[8] In our baseline analysis, micro-area refers to municipalities in the Netherlands, Switzerland, Sweden and Austria, counties in Germany, lower tier local authorities in Great Britain and provinces in Italy.

[9] The threshold value is set at the NUTS-3 level because we want to treat countries symmetrically when defining the sample start. Our micro-areas refer to different types of jurisdictions (e.g. counties in Germany but municipalities in Switzerland), so imposing a common threshold value for micro-areas would lead to a different coverage across countries. NUTS-3 regions are instead harmonized across countries and enable us to adopt a symmetric approach.

sufficiently low geographical levels.[10] We obtained data at the municipal level for Italy, the Netherlands and Sweden, and on the lower tier local authority level for Great Britain (see Appendix Table A.3). Excess mortality measures the number of deaths in a period minus the average number of deaths in the same period between 2015 and 2019.[11] The evolution of daily excess mortality per 100,000 inhabitants at the national level until June 2020 is visualized in Appendix Figure A.2.

Social capital. We hypothesize that social capital can slow down the spread of the virus, as individuals with higher social capital behave more socially responsible. In the context of this study, our concept of social capital refers mainly to "bridging social capital" (Putnam, 2000; Schmitt and Eijk, 2007), termed also "linking" social capital (Szreter and Woolcock, 2004) or civic capital (Guiso et al., 2011) in the more recent literature.[12]

We proxy social capital by standard measures put forward in the literature which mainly capture the bridging dimension of 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; Guiso et al., 2004; Bauernschuster et al., 2014). An extensive literature documents that political participation strongly correlates with 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) and it has been shown to be a particularly suitable proxy for social capital. As Guiso et al. (2011) put it, "[s]ince there is no direct economic payoff to voting, this measure captures the extent to which people in a community are willing to pay a personal cost to enhance the common good". A crucial advantage of turnout as a measure of social capital is that it is valid even at very disaggregated geographical levels, where other common measures, which are often based on surveys, would suffer from low representativeness.

We use turnout in European elections as our main outcome because it enables us to use data from the same election in all but one country.[13] A large and long-standing literature in political science subsumes that turnout in national and European elections is driven by similar motives (see, e.g., Schmitt and Eijk, 2007; Schmitt and Mannheimer,

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[10] Germany, Switzerland and Austria only publish mortality data at the state level. Furthermore, according to Economist (2020), they suffered a substantially lower number of excess deaths per 100,000 inhabitants (Switzerland 8, Germany 9 and Austria 11) than the other countries in our sample in the first wave (Netherlands 58, Sweden 62, Italy 87 and Britain 99). The combination of coarse geographical variation and a low number of deaths makes a systematic analysis impossible.

[11] The Netherlands only publish data at the municipality level for 2019 and 2020.

[12] The literature distinguishes two broad types of social capital: *bonding* and *bridging* social capital (Putnam, 2000; Schmitt and Eijk, 2007). While the former captures within-group solidarity, the later highlights across-group solidarity. According to, e.g., Putnam, 2000 and Satyanath et al., 2017, bonding social capital can have adverse effects and can turn out to be exclusive, while bridging social capital should always have beneficial effects.

[13] For Switzerland, we use data on turnout in the 2019 national elections.

1991; Steinbrecher and Rattinger, 2012). Moreover, a more recent strand of social capital studies argues that European election turnout is a particularly good proxy to capture civic duty as decisions at the European level are perceived to be more remote and have less of an effect on people's everyday life. Hence, political responsibility and the enhancement of the common good is a relatively more important factor to explain turnout (see, e.g. Bracco et al., 2015). Consistently, Blais and Galais (2016) document that the feeling of civic duty to vote (civic capital) is a particularly strong predictor of turnout in European elections.

As alternative measures of social capital, we use blood donations and registered organ donors per capita, which are also widely used in the literature (Guiso et al., 2004; Putnam, 1993). Due to data availability, we cannot apply the same measure for all countries. We use blood or organ donations for Great Britain, Italy and the Netherlands. Moreover, we use other common measures of social capital, such as the number of all registered associations per capita in Germany (Buonanno et al., 2009; Giuliano and Wacziarg, 2020; Satyanath et al., 2017) and historical literacy rates in Italy (Tabellini, 2010). Overall, our results are not driven by the choice of the social capital measure, as shown in Section 4.2.[14]

Controls. We test the sensitivity of our results to potential confounders in all countries 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 Appendix Tables A.1 and A.2 for details and descriptive statistics). Importantly, our specification allows for the influence of these variables to change over the course of the pandemic.

2.2 Policy responses and timing of effects

The timing of the Covid-19 outbreak and the respective policy responses differs across countries. Moreover, the adopted policy measures vary in strictness. While Italy enforced a strict and long lockdown during the first wave, Sweden did not adopt any kind of lockdown. Eventually, six of the seven countries under study implemented a national lockdown during the first wave, which was stricter than comparable U.S. "stay-at-home" orders. We highlight the most important events in each country in Appendix Table A.4.

Any change in behavior or policy will affect the number of Covid-19 cases with a time lag. First, there is the incubation time – the time from the infection until the appearance of first symptoms. Second, there is the confirmation time – the time between the first

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[14] The fine geographical level used in our analysis is important for identification. At the same time, it does not permit us to use common survey-based measures of social capital, such as social trust in the World Values Survey, as these measures are not available at the NUTS-3 or municipal level.

symptoms and the medical confirmation of the case. Naturally, both periods differ across individuals, countries and over time. 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 likely affect Covid-19 cases after around 12 days. This conclusion clearly entails a lot of uncertainty. For this reason, we do not use the "incubation plus confirmation" period of 12 days as a rigorous measure in our analyses, but rather as a plausible visual guideline in the graphical representations of our results.

2.3 Descriptive evidence

First, we investigate the descriptive pattern of the spread of Covid-19 and its relationship with social capital across countries. We dichotomize social capital into high-social-capital micro-areas (above-regional-median turnout) and low-social-capital micro-areas (below-regional-median turnout) for each country. We define the ratio of the number of log cases per capita in high- relative to low-social-capital micro-areas within each region 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 relative to low-social-capital micro-areas over time. Across all countries, we see that the virus is initially more prevalent in high-social-capital micro-areas. The initially high level is to be expected. People in areas with a high level of social capital have been shown to have closer social and economic connections (see, e.g., Knack and Keefer, 1997; Tabellini, 2010). This should exacerbate the spread of the virus initially when information on the severity of the virus and appropriate behavior is incomplete.

Starting from this high initial level, we then see a sharp decline in the ratio. Over time, the ratio drops until high-social-capital micro-areas have less than or almost equally many cases per inhabitant as low-social-capital micro-areas. Importantly, the decline starts before national lockdown policies could have been effective. This is a first indication that high- and low-social-capital micro-areas differ systematically in their socially responsible behavior.

Figure 1: Cumulative Covid-19 cases in high- relative to low-social-capital micro-areas
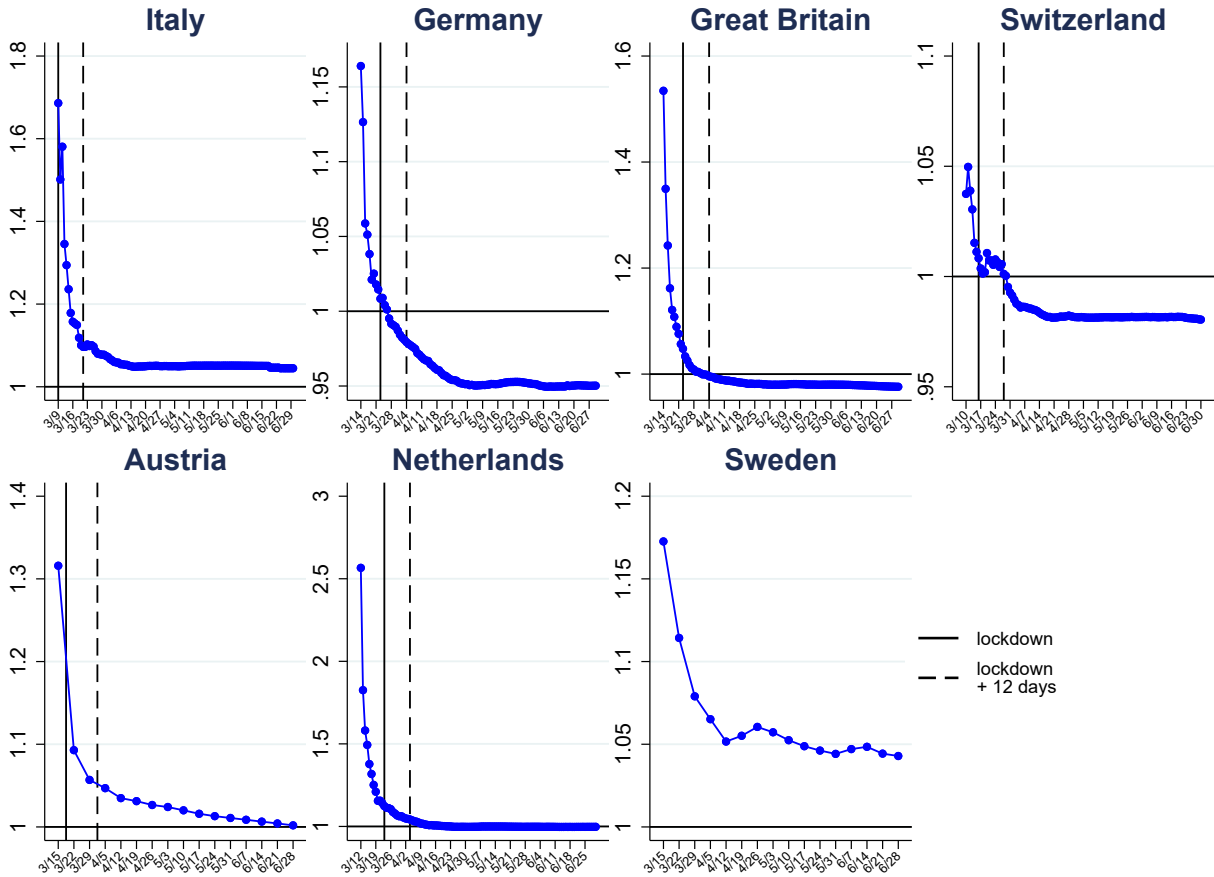
Notes: This figure shows the ratio of log cumulative Covid-19 cases per capita in high- vs. low-social-capital micro-areas. The sample is divided at the median of turnout at the NUTS-1 region level. Micro-areas with a value above the median are defined as high-social-capital micro-areas and those below as low-social-capital micro-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.

3   Empirical model and identification

3.1   Baseline regression model for Covid-19 cases

While Figure 1 presents simple correlations over time, we use the following more rigorous empirical model to systematically study the evolution of the relationship between social capital and the spread of the virus in each country. Our main outcome is the log cumulative number of cases per 100,000 inhabitants in micro-area a (within NUTS-1 region r) on day d, $\ln cumcases_{ad}$. As stated in Goodman-Bacon and Marcus (2020), the logarithmic model is suitable to capture the exponential growth of the virus and additionally helps to difference out measurement error in the outcome variable, which might be relevant when looking at Covid-19 cases. In order to identify the impact of social capital, we regress log cumulative Covid-19 cases on a pre-determined measure of social capital, $SocCap_a$, in a two-way fixed effects model. We estimate the following equation, separately for each

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country:

$$\ln(cumcases_{ad}) = \sum_d \beta_d \cdot date_d \cdot SocCap_a + \gamma_a + \sum_d \mu_d \cdot date_d \cdot region_r^{NUTS1} + \varepsilon_{ad}. \quad (1)$$

Our baseline model includes both area fixed effects γ_a, which absorb time-invariant heterogeneity, and region-by-date fixed effects $date_d \cdot region_r^{NUTS1}$, where the region dummy $region_r^{NUTS1}$ refers to the NUTS-1 region (see Section 3.2 for a more detailed discussion on the important role of these fixed effects).[15] We cluster the standard errors at the micro-area level in all specifications.

We proxy for social capital with micro-area-specific turnout in the European Parliament election of 2019, which we normalize by its country-specific standard deviation.[16] We interact social capital with date fixed effects to capture the dynamics of the effect of social capital on Covid-19 cases. Accordingly, a one-standard-deviation increase in social capital affects the number of cumulative cases per 100,000 inhabitants measured at date d by approximately $100 \times \beta_d$ percent. Hence, the β coefficients compare the evolution of micro-areas with a higher to those with a lower turnout over time, and relate the differences in log cases to the level of social capital. Loosely speaking, the empirical model (1) investigates the slope of the country-specific patterns in Figure 1. 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. We set the last day of the sample, d^{max}, to June 30, when the first wave of the pandemic had ended in all countries.[17]

3.2 Identification

In the context of our study, treatment status is defined by pre-determined social capital. Our identifying assumption is that no other factors correlated with social capital systematically affect growth rates of Covid-19 cases. While this assumption is untestable, we make various efforts to show that it is likely to hold.

First, our baseline model includes region-by-date fixed effects. These fixed effects flexibly control for any policy response at the regional level, such as periods of state-specific lockdowns, school closures, or test strategies, which were implemented in many countries at the NUTS-1 level. Hence, our estimates compare the evolution of micro-areas within a NUTS-1-region, accounting for any confounding shock at this regional level. The variation in most other European studies on the role of social capital is at the NUTS-1 region level,

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[15] In Switzerland, the whole country is a NUTS-1 region. We therefore perform a robustness check with more granular NUTS-3 fixed effects. The results in Appendix Figure C.3 are very similar to the baseline in Figure 2.

[16] As discussed in Section 2, we use alternative measures in Section 4.2 to show that our results are not driven by the choice of the social capital proxy.

[17] In a robustness check, we extend our sample until December 31 and thus include the second wave (see Appendix Figure C.2).

so it is difficult to disentangle policy from social capital effects.

Another concern is that area-specific outbreak dates vary and that areas may be on different points of their respective infection curves on a given day. Without further adjustments, our model in equation (1) would not be able to identify the causal effect of social capital if (i) area-specific outbreak dates were correlated with social capital and (ii) cases evolved according to a common epidemiological path. We address this challenge as follows. First, we document only a weak correlation of -0.09 between social capital and the start date within regions across countries. Second, despite the weak correlation, we propose a straightforward econometric fix to flexibly account for potentially remaining biases: we augment equation (1) by weeks-since-outbreak fixed effects. These fixed effects synchronize the outbreak dates of the micro-areas by accounting for the average pattern of an outbreak over time. We even go one step further and interact the weeks-since-outbreak fixed effects with date fixed effects ($weekssinceoutbreak_{ad} \cdot date_d$). This allows for changing outbreak patterns over time, for instance due to new information about the virus.[18]

In order to validate that our reduced-form model is able to cope with the challenges of using Covid-19 cases as a dependent variable, we set up a simple SIR model in Appendix B. First, we show that our estimates would indeed be biased if the outbreak date was correlated with social capital and we did not account for time-since-outbreak effects. However, as Appendix Figure B.3 shows, the inclusion of time-since-outbreak fixed effects can correct for that bias. Empirically, it turns out that the inclusion of weeks-since-outbreak-times-day fixed effects hardly affects our estimates. This is due to the weak correlation of social capital and area-specific outbreak dates across micro-areas.

Despite our large set of fixed effects, which account for regional policies and area-specific outbreak patterns, we assess whether omitted variables below the NUTS-1 level might drive our results by adding the most obvious potential confounders X_a to our baseline model. We do this symmetrically in all countries. More precisely, we add (i) education (more skilled people understand more quickly what is at stake); (ii) age structure (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 variables and interact each covariate with day fixed effects. This allows the impact of the given variable to depend on the phase of the pandemic, just as the effect of social capital.

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[18] Casting the model in event time, where the event is the first case in a specific area, is interesting but not ideal for the research question of this study, as we seek to estimate the impact of social capital on the spread of the virus for given information set about the severity of the virus and given policies in place.

Eventually, our most restrictive model is given by

$$\ln(cumcases_{ad}) = \sum_d \beta_d \cdot date_d \cdot SocCap_a + \gamma_a + \sum_d \mu_d \cdot date_d \cdot region_r^{NUTS1}$$
$$+ \sum_d \delta_d \cdot date_d \cdot weekssinceoutbreak_{ad} + \sum_d \alpha_d \cdot date_d \cdot X_a + \varepsilon_{ad}. \quad (2)$$

Comparing the point estimates of the baseline model in equation (1) with the extended model in equation (2) gives an indication of whether the identifying assumption is likely to hold. If the point estimates are relatively stable, this indicates that obvious unobserved confounders at higher regional levels (absorbed by the fixed effects) and observed confounders at the micro-area level are not driving our estimates. Last, we assess the likelihood that our estimates might be driven by unobserved confounders at the micro-area level by applying the test suggested by Oster (2019). The results suggest that our estimates are unlikely to be overturned by such unobserved confounders (see Section 4.2 for a more detailed discussion).

There are three important issues that arise when using Covid-19 cases as the main outcome. First, we can only assess the dynamics of the pandemic and their relation to social capital when a large enough share of areas has been hit with the virus. There is a clear trade-off between – on the one hand – starting the sample earlier and capturing the early pandemic dynamics related to social capital and – on the other hand – obtaining precise estimates of these early dynamics that are informed by a meaningful number of micro-areas. In our baseline specification, our sample starts on the day when 90% of all NUTS-3 regions have registered at least one Covid-19 case. In a robustness check we show that our point estimates vary slightly but remain consistently negative with other thresholds (see Appendix Figure C.4). As expected, we lose precision when choosing an earlier sample start.

Second, one may be concerned that an initially higher level of cases in high-social-capital micro-areas might mechanically lead to a slower spread of the pandemic in these areas in the subsequent periods (cf. Figure 1). In Appendix B, we show that initial level differences between high- and low-social-capital areas at the sample start, i.e. high-social-capital areas having higher infection rates in the early phase of the pandemic, rather lead to a conservative estimate of the effect of social capital. The SIR model shows that a higher relative level of Covid-19 cases in high-social-capital areas is associated with a weaker effect of social capital on the spread of the virus. The intuition is that a higher number of infected individuals makes every contact riskier.

Third, we study the early dynamics of a pandemic caused by a new virus, so there is no pre-outbreak period. However, one testable implication of our identification assumption is that high- and low-social-capital micro-areas do not already diverge in terms of health outcomes (unrelated to Covid-19) before the outbreak of the pandemic. To assess whether areas

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with high social capital were on different health trends before, we use excess mortality as an alternative outcome (see Section 3.3). Moreover, we extend our analysis to the second wave. During the summer of 2020, we observe low but positive numbers of Covid-19 cases in all micro-areas across countries and can inspect the dynamics leading up to the second wave.

3.3 Regression model for excess mortality

If higher social capital slows down the spread of Covid-19 cases, we would also expect to see an effect on mortality. As described in Section 2, our preferred measure of mortality is the log cumulative number of excess deaths per 100,000 inhabitants, $\ln excessdeaths_{ad}$ (Aron and Muellbauer, 2020; Ciminelli and Garcia-Mandicó, 2020). Excess mortality is calculated by comparing the number of deaths in micro-area a on date d in 2020 to the number of deaths in the same micro-area and on the same date in previous years. Using excess deaths as a measure of mortality is preferable to official Covid-19 death counts, as the latter measure is likely to underestimate the true increase in mortality (Ciminelli and Garcia-Mandicó, 2020).

Moreover, the number of excess deaths does not depend on testing capacities, which might theoretically vary with social capital. Finally, data on excess deaths are available at very fine geographic levels for the Netherlands, Great Britain, Italy and Sweden, allowing us to control flexibly for potential confounders. More specifically, for Italy, the Netherlands and Sweden we have data at the municipality level and include NUTS-3-by-time fixed effects.[19] While excess mortality is a natural additional health outcome to study, it is also interesting for econometric reasons, since it enables us to assess whether there are different health trends between high- and low-social capital areas leading up to the outbreak of the pandemic (cf. Section 3.2).

Using an analogous notation as in equations (1) and (2), the corresponding regression model is given by:

$$\ln excessdeaths_{ad} = \sum_d \beta_d \cdot date_d \cdot SocCap_a + \gamma_a + \sum_d \mu_d \cdot date_d \cdot region_r^{NUTS3}$$
$$+ \sum_d \alpha_d \cdot date_d \cdot X_a + \varepsilon_{ad}. \tag{3}$$

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[19] For Great Britain, we use NUTS-1-by-time fixed effects, as the data are reported at the NUTS-3 level. Note that the data do not include Scotland, which only publishes death statistics on a monthly basis.

4 Empirical findings

4.1 Main results

Figure 2 visualizes the β coefficients from equation (1). Across all countries, we see a consistent pattern: high-social-capital micro-areas exhibit a slower growth of cumulative cases than low-social-capital micro-areas. A one-standard-deviation increase in social capital reduces the cumulative number of Covid-19 cases in micro-areas over the considered period by 14% ($p < 0.01$) in Germany, 20% ($p < 0.01$) in Austria, 21% ($p < 0.05$) in Sweden, 24% ($p < 0.01$) in Great Britain, 24% ($p < 0.01$) in Switzerland, 28% ($p < 0.01$) in the Netherlands and 34% ($p < 0.05$) in Italy.

Overall, we interpret the consistent pattern and statistically significant results 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.

Moreover, our empirical model enables us to analyze the dynamics of the effect of social capital in detail. Figure 2 clearly shows that micro-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 any effect: assuming an incubation plus confirmation time of about 12 days (cf. Section 2.2), Figure 2 shows that the bulk of the effect has already materialized before the 12 days following the national lockdown are reached.

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 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 argument is further supported by the Swedish results. As Sweden is the only country that did not implement a national lockdown, social capital should matter over the whole sample period. Correspondingly, the decline in Sweden is more continuous and does not flatten over time. This pattern becomes even clearer when looking at the second wave in Appendix Figure C.2.

Figure 2: Effect of social capital on the spread of Covid-19 cases
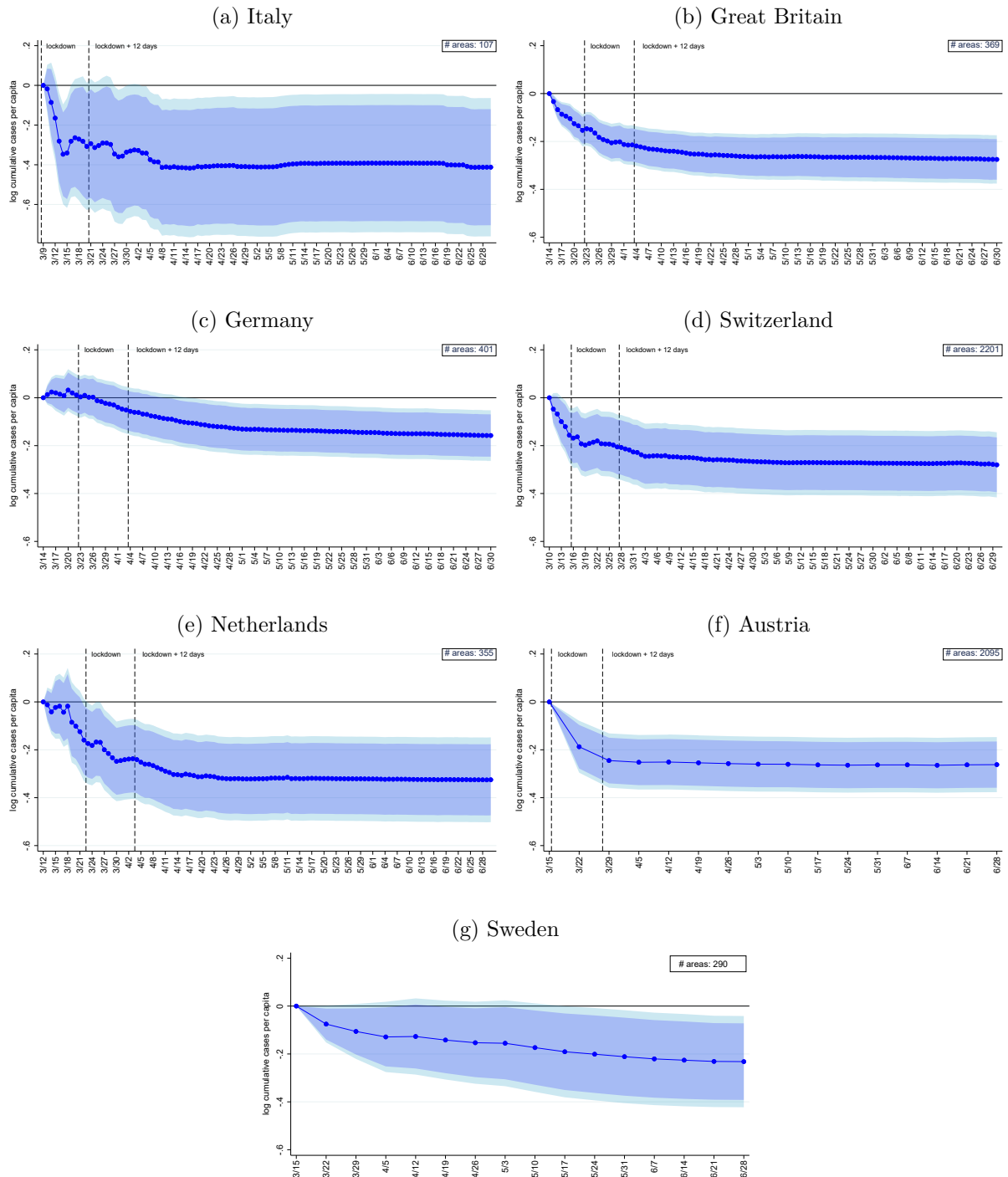
Notes: The figure presents the differential evolution of the relationship between cumulative Covid-19 infections per 100,000 inhabitants and social capital across time. The estimates are based on the model outlined in equation (1) (see Appendix Table C.1 for the point estimates). The first dashed line 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.

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

(a) Italy

(b) Great Britain

(c) Germany

(d) Switzerland

(e) Netherlands

(f) Austria

(g) Sweden
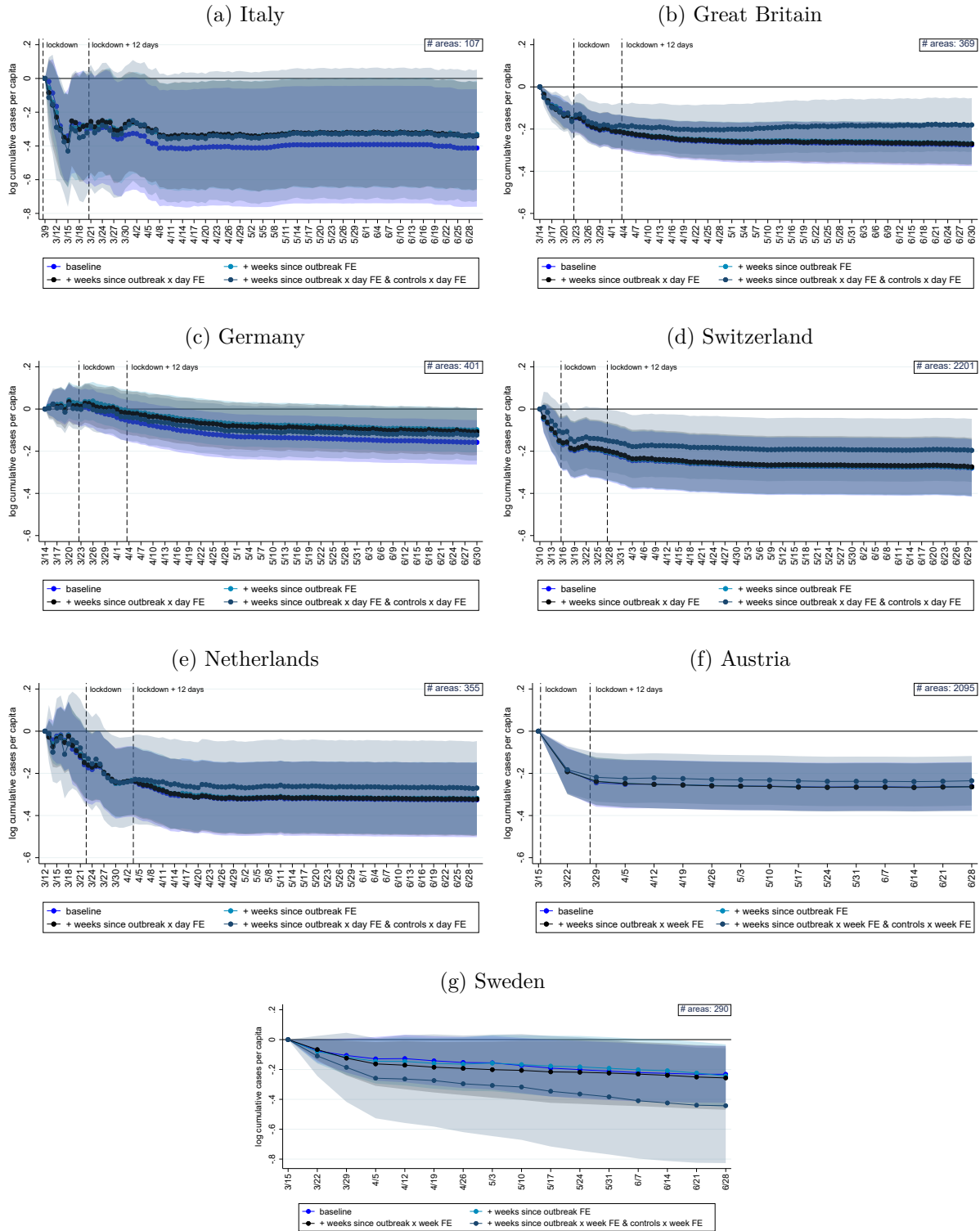
Notes: This graph shows alternative specifications for the results reported in Figure 2. The dark blue line reports the baseline results in Figure 2 (see Appendix Table C.1 for point estimates). The light-blue line includes weeks-since-outbreak fixed effects; the black line includes weeks-since-outbreak x date fixed effects. The grey line additionally includes a set of controls interacted with date 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.

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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 could wrongly attribute their effects to social capital. As discussed in Section 3.2, we test the sensitivity of our results by adding (i) different sets of (time-since-outbreak) fixed effects and (ii) obvious confounding variables interacted with day fixed effects (cf. equation (2)).

Figure 3 shows the resulting estimates. Magnitudes, dynamics and statistical significance are generally similar across specifications, which is a first indication that further unobserved confounders are unlikely to drive the results.[20]

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^2 across specifications. We apply the suggested bounding exercise to the last point estimate $\beta_{d^{max}}$ of our dynamic model (1). Appendix Table C.4 shows that all bounded estimates stay negative and close to our baseline estimates 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.[21]

Alternative social capital measures In order to validate that our results are not driven by the choice of our proxy for social capital, we assess the sensitivity of our estimates with respect to alternative social capital measures. Apart from turnout, the literature has validated blood and organ donations as useful proxies of social capital (see, e.g., Guiso et al., 2004; Putnam, 1993). For Italy and Britain, we obtained sufficiently fine-grained data on blood donations. For the Netherlands, we obtained data on the number of registered organ donors willing to donate (see Appendix Table A.1 for details). Panels (a) to (c) of Figure 4 show that the results are similar when using these alternative measures.

As no comparable data are available for Germany, we use the density of associations, another widely used proxy (Putnam, 2000; Satyanath et al., 2017). Panel (d) shows a very similar effect on Covid-19 cases 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 that influence social capital to this day (see, e.g.,

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[20] For better readability of the precision across specifications, Appendix Table C.1 reports the last dynamic estimate for each country with standard errors for each specification.

[21] Based on self-collected survey data from the U.S., Barrios et al. (2021) show that fear cannot explain the association between changes in mobility and social capital. Durante et al. (2021) reach the same conclusion, using the distance to regional hotspots as a proxy for fear.

Figure 4: Alternative social capital measures
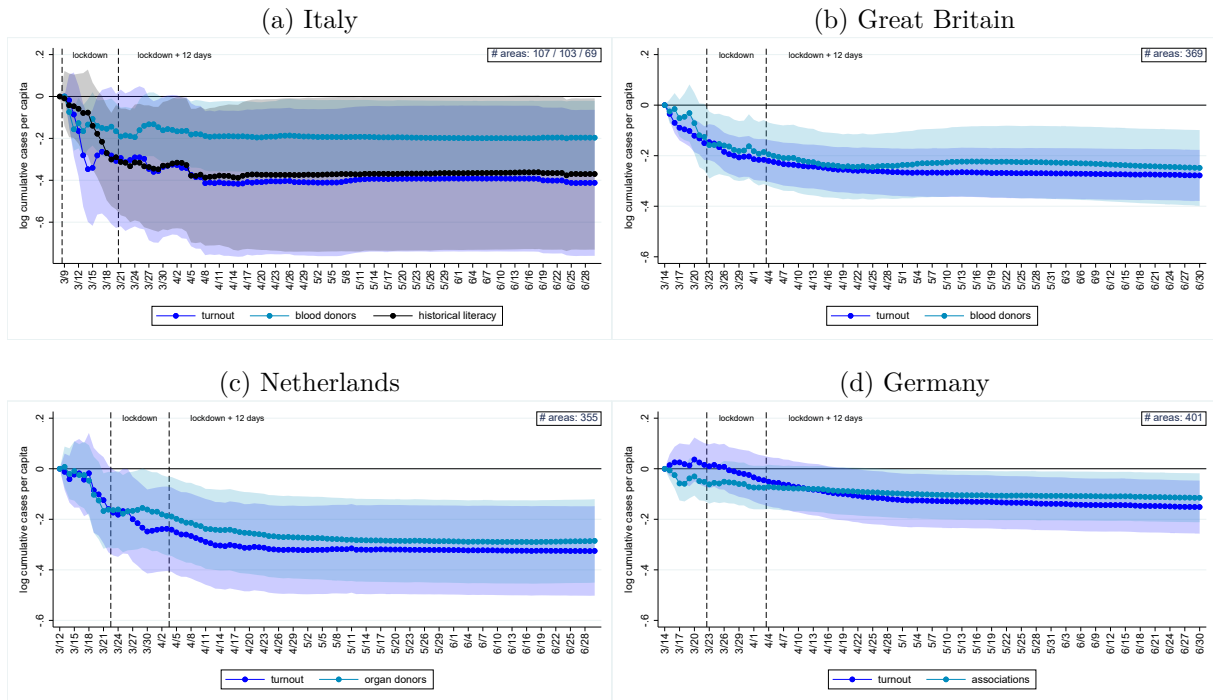
(a) Italy

(b) Great Britain

(c) Netherlands

(d) Germany

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. As measure of social capital, in panel (a) we use turnout, literacy rates in 1821 and blood donations per capita, in panel (b) we use turnout and blood donations per capita, in panel (c) we use turnout and the number of registered organ donors per capita, in panel (d) we use turnout and associations per capita (see Appendix Table C.3 for point estimates).

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 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).[22] This measure again yields a very similar pattern (see Figure 4). Appendix Figure C.1 confirms that our results are again robust to the inclusion of additional fixed effects and controls.

Excess mortality. Additionally, we present the results from using excess mortality as an alternative Covid-related health outcome, estimating equation (3). Figure 5 shows that by the end of June 2020, a one-standard-deviation increase in turnout is significantly associated with fewer accumulated excess deaths per 100,000 inhabitants in Italy, the

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[22] As we operate at least at the NUTS-3 level, we could not use the data in Tabellini (2010), which cover NUTS-1 or NUTS-2 regions across Europe. We transformed our data to the province borders of 1911 (see Appendix Table A.1 for details).

Figure 5: Effect of social capital on excess deaths
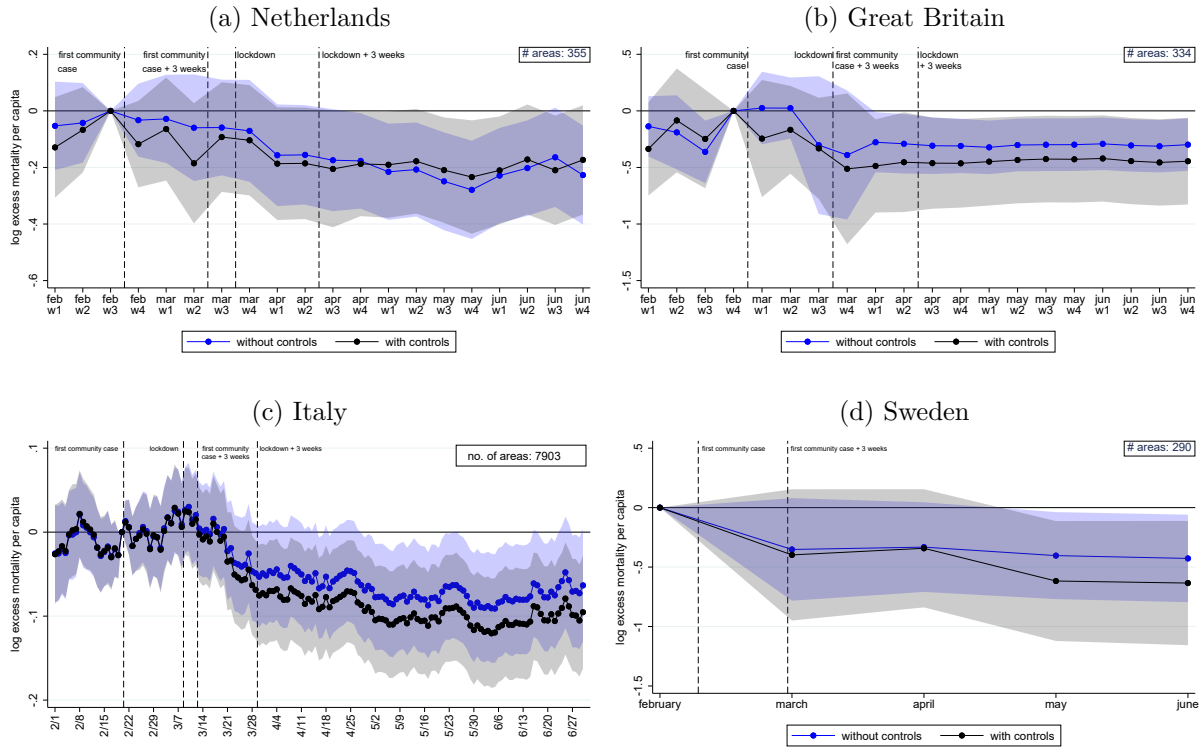
(a) Netherlands

(b) Great Britain

(c) Italy

(d) Sweden

Notes: The figure presents the differential evolution of the relationship between cumulative excess deaths per 100,000 inhabitants and social capital over time. The estimates are based on the model outlined in equation (3) including NUTS-3 x time FE instead of NUTS-1 x time FE (see Appendix Table C.5 for the point estimates). The shaded areas correspond to the 95% confidence interval.

Netherlands, Sweden and Great Britain. The effect size ranges from 6% in Italy to 35% in Sweden and stays relatively similar when including control variables (see Appendix Table C.5). The estimates imply that a one-standard-deviation increase in social capital could have prevented 1,632 deaths in Sweden, 1,787 deaths in the Netherlands, 2,823 deaths in Italy, and 14,303 deaths in Great Britain. Reassuringly, excess mortality before the pandemic evolves in parallel between high- and low-social-capital micro-areas, which lends support to our identifying assumption.[23]

In terms of dynamics, Figure 5 corroborates the evidence shown in Figures 1 and 2: the number of excess deaths in high-social-capital micro-areas starts to drop around the time of (or even before) the national lockdown. This decrease 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 micro-areas about two to three weeks after the first community case. Moreover, effects stabilize about three weeks after the lockdown. This pattern is in line with evidence that deaths tend to occur around three weeks after the infection (Yang et al., 2020) and points to the specific role

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[23] Figure C.5 in the Appendix shows a consistent pattern holds for Sweden when using data in 10-day blocks, which are only available from 2018 to 2020.

of social capital in the absence of strict policy measures.

Extension to the second wave Last, we extend our dataset on Covid-19 cases until the December 31, 2020 to additionally examine the effect of social capital in the second wave, which hit the countries under study in the fall. To this end, we estimate equation 1 on the extended sample. We measure the effect of social capital during the second wave by testing for the difference between the estimate on December 31, 2020 and the estimate on the June 30, 2020. The latter date marks the last day of our baseline sample, when the first wave had receded in all countries (see Appendix Figure A.1). During the summer months the case numbers were low but positive in all countries. Hence, we can observe whether cases in high- and low-social-capital micro-areas evolve similarly before the second wave starts. Appendix Figure C.2 plots the estimates for all countries, together with an estimate of the additional impact of social capital during the second wave. In six out of the seven countries, we observe an additional social capital effect during the second wave. A one-standard-deviation increase in social capital leads to an additional reduction in cumulative cases per 100,000 inhabitants of 4% ($p < 0.05$) in Switzerland, 7% ($p < 0.05$) in the Netherlands, 7% ($p < 0.01$) in Great Britain, 10% in Germany ($p < 0.01$), 21% in Sweden ($p < 0.05$) and 28% in Italy ($p < 0.01$). It is only for Austria that we do not observe a significant additional effect during the second wave. The pattern of the effect is very similar to the first wave. In all cases, the effect materializes before the lockdowns during the second wave could have had any effect, as indicated by the dashed lines. This underscores our interpretation that social capital is particularly important in the absence of strict lockdowns. This interpretation is reinforced by the pattern of the Swedish estimates: in the absence of a lockdown, the effect grows continuously over the whole sample period.

5 Conclusion

In this paper, we provide evidence from seven European countries that social capital has a considerable impact on the spread of Covid-19 cases and the number of excess 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 suggests that a higher level of social capital also has an indirect positive effect on the economy during and after the crisis (Barro, 2020; Barro et al., 2020).

Our results have important implications for policymakers. Given the faster spread of the virus in areas with lower social capital, it may help to launch targeted information

campaigns and health education programs in these areas. It its important to note that social capital is likely to remain relevant even after vaccines are widely available because the willingness to get vaccinated is a public good just as the willingness to practice social distancing (Chuang et al., 2015; Jung et al., 2013; Rönnerstrand, 2014; Schmelz and Bowles, 2021).

Our results also imply that social capital formation is an important insurance against similar future pandemics. Hence, the insights from our study should encourage policy-makers to invest not only in the health system, but also in building social capital to be well prepared. Possible points of departure are social components in transfer programs, or local community programs to increase social exchange, 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., 2013).

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A Data Appendix

Table A.1: Definition of variables and data sources

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

continued

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

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

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

Table A.2: Summary statistics

	mean	p25	p75	sd	min	max	N
Austria: municipality level							
turnout	0.54	0.47	0.60	0.08	0.24	0.84	2095
population (in 100,000)	0.04	0.01	0.03	0.43	0.00	19.11	2095
population density (in 1,000/km^2)	0.14	0.04	0.13	0.27	0.00	4.60	2095
GDP per capita (in 1,000€)	37.01	29.60	44.60	8.71	23.00	54.50	2095
hospital beds per 1,000 inhabitants	3.50	0.00	0.00	20.86	0.00	408.72	2095
share white-collar	0.18	0.14	0.21	0.05	0.04	0.36	2095
share old	0.20	0.17	0.22	0.04	0.10	0.40	2095
share educated	0.31	0.27	0.35	0.06	0.13	0.62	2095
Germany: county level							
turnout	0.61	0.57	0.64	0.05	0.48	0.74	401
associations per 1,000 inhabitants	6.88	5.67	7.81	1.97	1.00	17.34	401
population (in 100,000)	2.07	1.04	2.42	2.48	0.34	37.54	401
population density (in 1,000/km^2)	0.43	0.09	0.52	0.57	0.03	3.91	401
GDP per capita (in 1,000€)	37.16	27.93	40.51	16.12	16.40	172.43	401
hospitals per 100,000 inhabitants	2.48	1.50	3.06	1.50	0.00	9.80	401
share white-collar	0.43	0.35	0.49	0.10	0.22	0.76	401
share old	0.22	0.20	0.24	0.03	0.16	0.32	401
share educated	0.32	0.27	0.38	0.09	0.12	0.58	401
Great Britain: lower tier local authority level							
turnout	0.37	0.34	0.40	0.05	0.23	0.54	369
blood donors per capita	0.01	0.01	0.02	0.01	0.00	0.03	369
population (in 100,000)	1.76	1.01	2.15	1.19	0.22	11.42	369
population density (in 1,000/km^2)	1.60	0.20	2.05	2.49	0.01	16.24	369
GDP per capita (in 1,000€)	33.55	23.48	36.77	24.75	15.40	309.99	369
hospitals per 100,000 inhabitants	1.17	0.00	1.47	1.51	0.00	11.23	369
share white-collar	0.18	0.14	0.22	0.07	0.08	0.50	369
share old	0.22	0.20	0.23	0.02	0.16	0.31	369
share educated	0.43	0.37	0.46	0.08	0.32	0.72	369
Italy: province level							
turnout	0.56	0.50	0.65	0.11	0.34	0.70	107
blood donations per capita	0.04	0.02	0.05	0.02	0.00	0.12	103
literacy rate in 1821	0.25	0.16	0.35	0.11	0.09	0.54	69
population (in 100,000)	5.64	2.35	6.22	6.17	0.84	43.42	107

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

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

Table A.3: Geographical units across countries

Covid-19 cases

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

Excess deaths

| country	micro-area (below NUTS-3)	# micro-areas	region (NUTS-3)	# regions
Great Britain	lower tier local authority	334	Wales and statistical regions of England (NUTS-1)	10
Italy	municipality (*commune*)	7903	province (*Province*)	107
Netherlands	municipality (*Gemeente*)	355	COROP regions (*COROP-gebieden*)	40
Sweden	municipality (*Sveriges kommuner*)	290	county (*Län*)	21

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

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

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

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

Figure A.1: Number of cases per 100,000 inhabitants at the national level over time
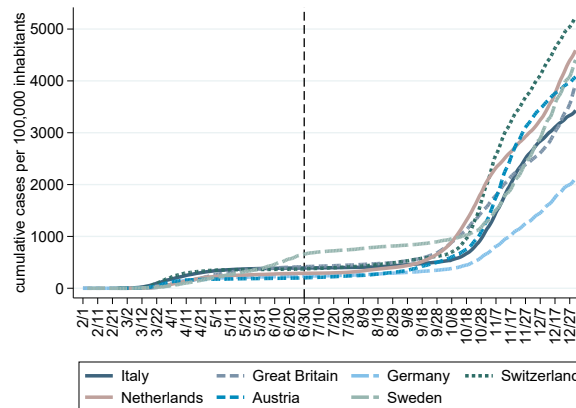
Notes: The graph shows the development of the pandemic for each country over time expressed as the number of infections per 100,000 inhabitants. The dashed line marks the end of our baseline sample.

Figure A.2: Number of excess deaths at the national level over time
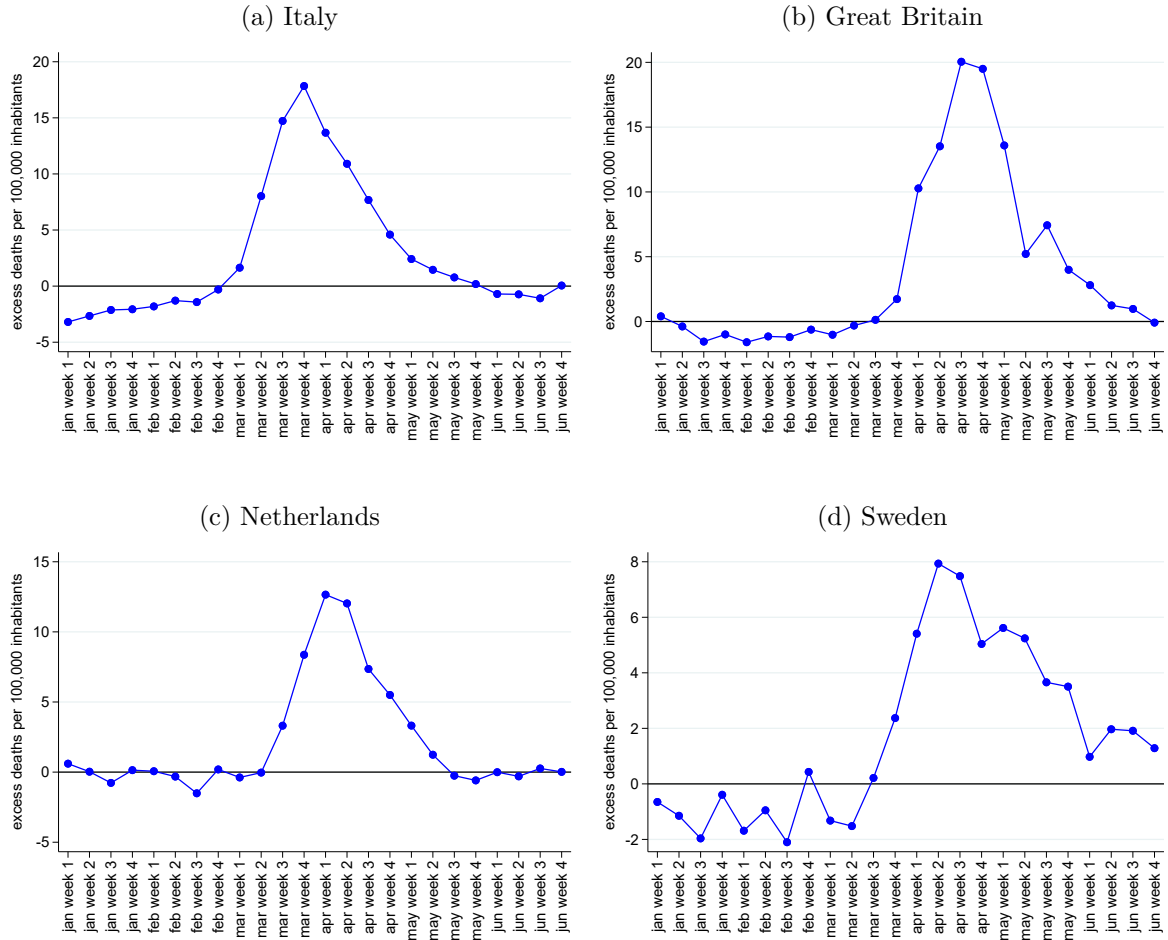
(a) Italy

(b) Great Britain

(c) Netherlands

(d) Sweden

B Simple SIR model

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

$$I_{t+1} = I_t + \beta_t S_t \frac{I_t}{N}$$
$$S_{t+1} = S_t - \beta_t S_t \frac{I_t}{N}$$
$$R_{t+1} = R_t + \gamma I_t \ .$$

The number of infected individuals I_{t+1} is determined by the contact rate β_t, multiplied with the stock of susceptible individuals S_t and already infected individuals I_t and divided

by the total population $N = S+I+R$. The change in the number of susceptible individuals is the mirror image of the change in infected individuals. Moreover, a fraction γ of the infected individuals recovers each day.

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

The contact rate beta is specified as $\beta_{ip} = \beta_0 \cdot exp(\alpha_p \cdot sc_i + \epsilon_{it})$ for $p \in \{1, 2\}$, where sc_i is social capital in area i, drawn from a normal distribution with mean zero and standard deviation 0.5, and $\epsilon_{it} \sim N(0, 0.2)$ is a random error term drawn for each area i and day t. We assume that during the first 7 days (phase 1), agents are unaware of the virus. In the baseline simulation, we set $\alpha_1 = 0$, meaning that the contact rate is initially the same everywhere. For γ and β_0, we choose the values 0.1 and 0.25, implying an initial basic reproduction number R_0 of 2.5. If α_1 was positive, a case which we will explore below, the spread of the virus would initially be greater in high- than in low-social-capital areas. In phase 2, agents become aware of the risks of the disease and adapt their behavior accordingly. We set $\alpha_2 = -0.3$, which implies that once agents become aware of the virus, those living in high-social-capital areas reduce their contacts by more compared to those in low-social-capital areas. Finally, in phase $p = 3$, starting on day 14, there is a lockdown, where all areas have the same contact rate $\beta_{i3} = \beta_0 \cdot exp(\alpha_3 + \epsilon_{it})$. We set $\alpha_3 = -1$, implying that the reproduction number will fall below 1 after the lockdown.[24]

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

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

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

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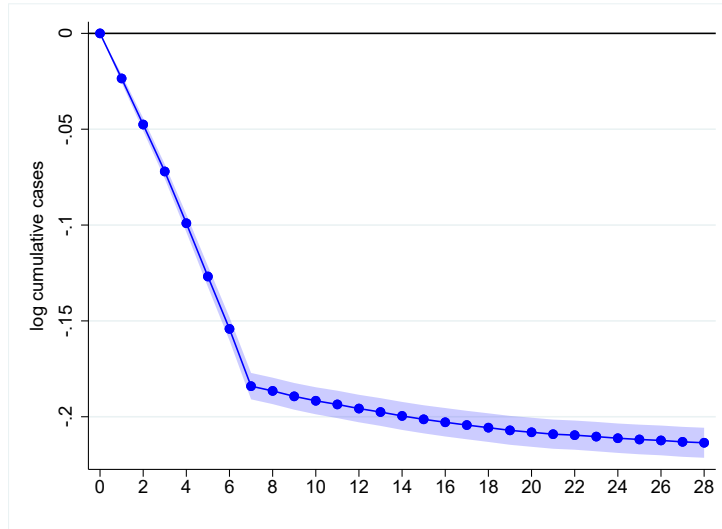
Notes: The graph shows the results from estimating our baseline model (1) on data simulated from the SIR model.

a similar growth trajectory.[25]

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

Figure B.2: Effect of differential initial growth

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

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

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

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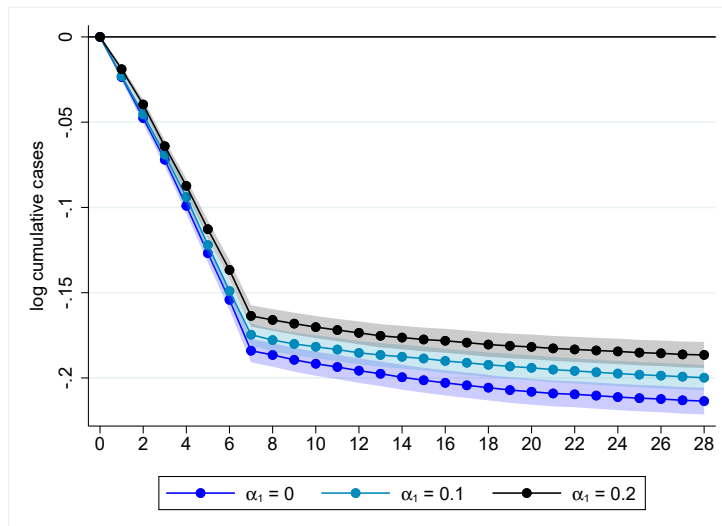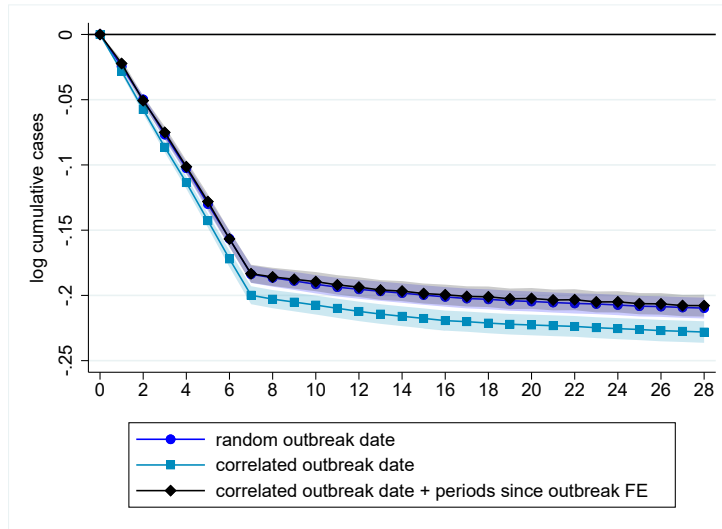

Notes: The graph shows the results from estimating our baseline model (1) on data simulated from the SIR model. The dotted blue line shows the results for the case of a random outbreak date. The squared light blue line shows results for the case when the outbreak date is correlated with social capital.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

In the second simulation exercise, we relax the assumption that the pandemic starts on the same day in each area. Here, the concern is that high- and low-social capital areas are at different points of the infection curve, such that our estimates do not pick up the effect of social capital, but these systematically different dynamics. We test whether period-since-outbreak fixed effects are able to account for the resulting bias. As a benchmark, we draw a random start date for each area from a uniform distribution between days 0 and 6. Next, we impose a negative correlation between the start date and social capital, such that high-social-capital areas are hit earlier by the virus. We set the correlation to a relatively high value of -0.5 for illustrative purposes.[26] We estimate both our baseline model and a model with period-since-outbreak fixed effects on the simulated data. Figure B.3 illustrates the effect of using the period-since-outbreak fixed effects. The dotted blue line shows the results for the case when the outbreak date is random. The squared light

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

blue line shows results for the same regression when the outbreak date is correlated with social capital. We see that in this case, the point estimates become slightly larger in absolute value, meaning that we would overstate the social capital effect. However, once we include period-since-outbreak fixed effects, we can recover the original estimates, as shown by the black line with diamonds.[27]

C   Additional Results

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

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

continued

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

Table C.1 continued

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

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

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

	(1)	(2)	(3)	(4)
Panel A − Italy				
turnout x 31dec2020	-0.756*** (0.229)	-0.661*** (0.211)	-0.660*** (0.213)	-0.578** (0.238)
province FE	yes	yes	yes	yes
NUTS1 x day FE	yes	yes	yes	yes
weeks-since-outbreak FE	no	yes	no	no
weeks-since-outbreak x day FE	no	no	yes	yes
controls x day FE	no	no	no	yes
mean	5.826	5.826	5.833	5.833
observations	31,862	31,862	31,615	31,615
Panel B − Great Britain				
turnout x 31dec2020	-0.349*** (0.052)	-0.341*** (0.050)	-0.344*** (0.050)	-0.232*** (0.067)
lower tier local authority FE	yes	yes	yes	yes
NUTS1 x day FE	yes	yes	yes	yes
weeks-since-outbreak FE	no	yes	no	no
weeks-since-outbreak x day FE	no	no	yes	yes
controls x day FE	no	no	no	yes
mean	6.034	6.034	6.034	6.034
observations	107,957	107,956	107,297	107,297
Panel C − Germany				
turnout x 31dec2020	-0.268*** (0.053)	-0.214*** (0.054)	-0.230*** (0.057)	-0.207*** (0.061)
county FE	yes	yes	yes	yes
NUTS1 x day FE	yes	yes	yes	yes
weeks-since-outbreak FE	no	yes	no	no
weeks-since-outbreak x day FE	no	no	yes	yes
controls x day FE	no	no	no	yes
mean	5.524	5.524	5.520	5.520
observations	116,813	116,813	116,102	116,102
Panel D − Switzerland				
turnout x 31dec2020	-0.349*** (0.070)	-0.380*** (0.070)	-0.368*** (0.070)	-0.240*** (0.080)
municipality FE	yes	yes	yes	yes
NUTS1 x day FE	yes	yes	yes	yes
weeks-since-outbreak FE	no	yes	no	no
weeks-since-outbreak x day FE	no	no	yes	yes
controls x day FE	no	no	no	yes
mean	6.253	6.253	6.253	6.253
observations	554,601	554,601	554,123	554,123
Panel E − The Netherlands				
turnout x 31dec2020	-0.380*** (0.094)	-0.387*** (0.091)	-0.374*** (0.091)	-0.325*** (0.115)
municipality FE	yes	yes	yes	yes

continued

Table *C.1* continued

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

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

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

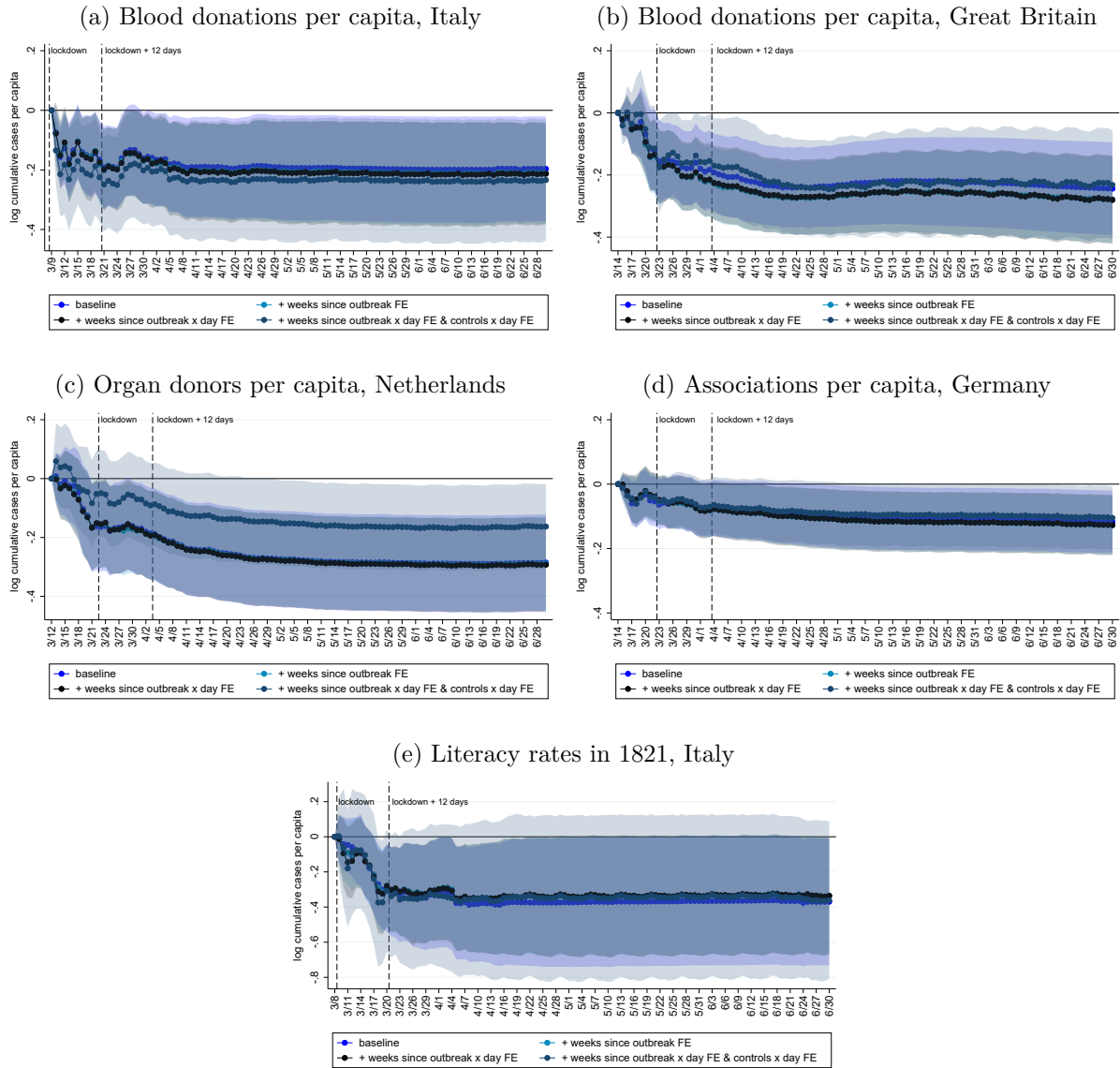|	(1)	(2)	(3)	(4)
Panel A − Italy				
blood donations per capita x 30jun2020	-0.197** (0.090)	-0.211** (0.086)	-0.213** (0.087)	-0.234** (0.104)
province FE	yes	yes	yes	yes
NUTS1 x day FE	yes	yes	yes	yes
weeks-since-outbreak FE	no	yes	no	no
weeks-since-outbreak x day FE	no	no	yes	yes
controls x day FE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

continued

Table C.3 continued

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

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

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

(a) Blood donations per capita, Italy

(b) Blood donations per capita, Great Britain

(c) Organ donors per capita, Netherlands

(d) Associations per capita, Germany

(e) Literacy rates in 1821, Italy

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

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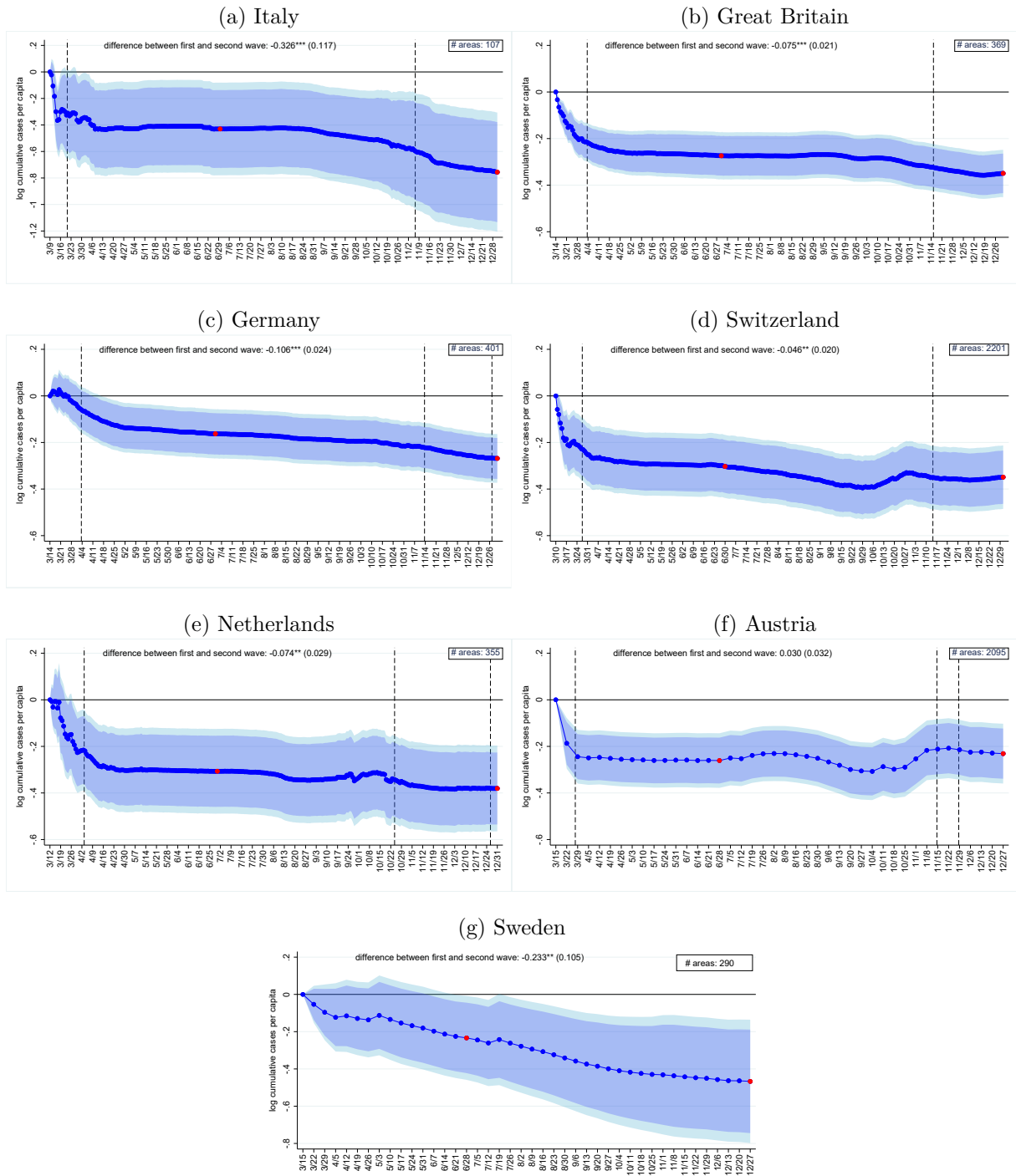
(a) Italy

(b) Great Britain

(c) Germany

(d) Switzerland

(e) Netherlands

(f) Austria

(g) Sweden

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

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

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

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

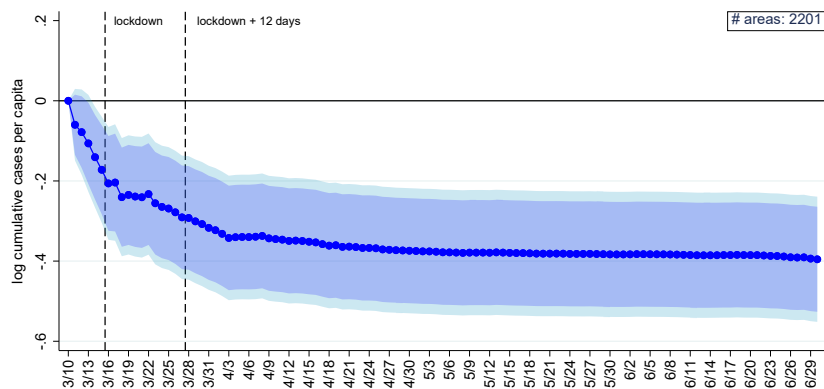**Figure C.3:** Effect of social capital on Covid-19 cases: Swiss municipalities with NUTS-3 fixed effects

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

Figure C.4: Effect of social capital on Covid-19 cases: by threshold
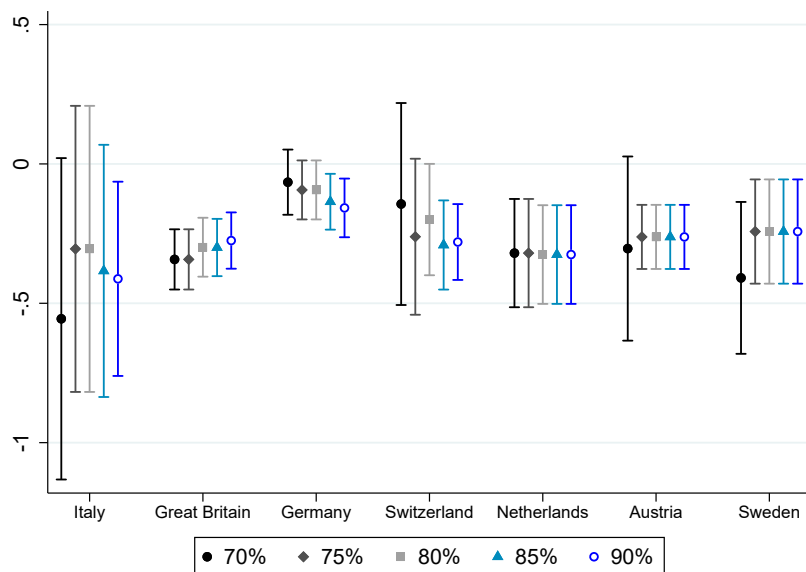
Notes: The figure plots the estimate on June 30 from equation (1) and the corresponding 95% confidence interval, varying the threshold criterion used to choose the start date of the sample for each country. The sample starts when more than a certain percentage from 70% to 90% of NUTS-3 regions in a country have experienced at least one case. Since we have weekly data for Austria and Sweden, the sample start always falls in the same week. Therefore, we shift the sample start backwards by one week for the 70% criterion for those countries.

Figure C.5: Effect of social capital on excess deaths: Swedish municipalities in 10-day blocks
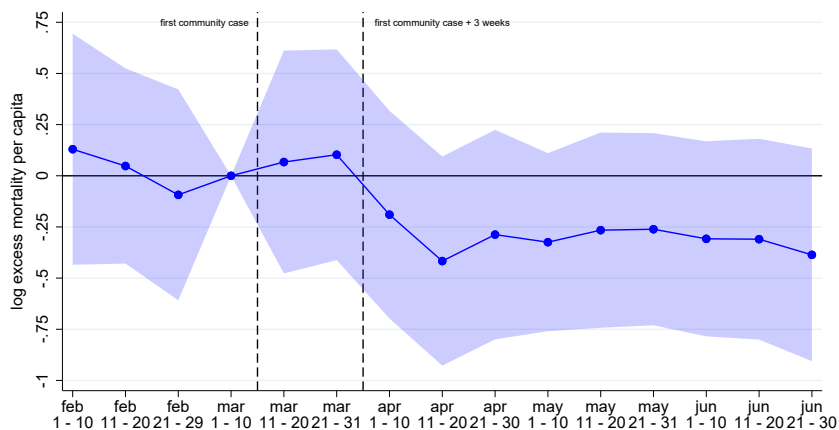
Notes: The figure presents the differential evolution of the relationship between cumulative excess deaths per 100,000 inhabitants and social capital across time. The estimates are based on the model outlined in equation (3). The shaded areas correspond to the 95% confidence interval.

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

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

continued

Table C.5 *continued*

	(1)		(2)	
turnout x 14mar2020	0.001	(0.028)	-0.009	(0.028)
turnout x 15mar2020	0.003	(0.029)	-0.005	(0.029)
turnout x 16mar2020	-0.003	(0.028)	-0.011	(0.029)
turnout x 17mar2020	0.016	(0.029)	0.010	(0.029)
turnout x 18mar2020	0.006	(0.029)	0.000	(0.029)
turnout x 19mar2020	-0.002	(0.029)	-0.010	(0.029)
turnout x 20mar2020	0.004	(0.029)	-0.005	(0.029)
turnout x 21mar2020	-0.023	(0.030)	-0.035	(0.030)
turnout x 22mar2020	-0.019	(0.029)	-0.034	(0.029)
turnout x 23mar2020	-0.037	(0.029)	-0.051*	(0.029)
turnout x 24mar2020	-0.038	(0.029)	-0.054*	(0.029)
turnout x 25mar2020	-0.041	(0.030)	-0.057*	(0.030)
turnout x 26mar2020	-0.039	(0.030)	-0.056*	(0.030)
turnout x 27mar2020	-0.025	(0.030)	-0.045	(0.030)
turnout x 28mar2020	-0.047	(0.030)	-0.063**	(0.030)
turnout x 29mar2020	-0.049*	(0.030)	-0.069**	(0.030)
turnout x 30mar2020	-0.053*	(0.031)	-0.075**	(0.031)
turnout x 31mar2020	-0.049	(0.030)	-0.073**	(0.030)
turnout x 01apr2020	-0.052*	(0.030)	-0.075**	(0.030)
turnout x 02apr2020	-0.046	(0.031)	-0.070**	(0.031)
turnout x 03apr2020	-0.049	(0.030)	-0.070**	(0.031)
turnout x 04apr2020	-0.044	(0.031)	-0.068**	(0.031)
turnout x 05apr2020	-0.051*	(0.031)	-0.077**	(0.031)
turnout x 06apr2020	-0.054*	(0.031)	-0.081***	(0.031)
turnout x 07apr2020	-0.054*	(0.031)	-0.080***	(0.031)
turnout x 08apr2020	-0.040	(0.031)	-0.067**	(0.031)
turnout x 09apr2020	-0.043	(0.031)	-0.071**	(0.031)
turnout x 10apr2020	-0.047	(0.031)	-0.073**	(0.032)
turnout x 11apr2020	-0.050	(0.031)	-0.076**	(0.032)
turnout x 12apr2020	-0.058*	(0.031)	-0.085***	(0.032)
turnout x 13apr2020	-0.053*	(0.031)	-0.079**	(0.031)
turnout x 14apr2020	-0.059*	(0.031)	-0.083***	(0.031)
turnout x 15apr2020	-0.049	(0.031)	-0.075**	(0.031)
turnout x 16apr2020	-0.067**	(0.031)	-0.092***	(0.031)
turnout x 17apr2020	-0.064**	(0.031)	-0.089***	(0.031)
turnout x 18apr2020	-0.053*	(0.031)	-0.077**	(0.031)
turnout x 19apr2020	-0.067**	(0.031)	-0.089***	(0.032)
turnout x 20apr2020	-0.059*	(0.031)	-0.082***	(0.032)
turnout x 21apr2020	-0.056*	(0.031)	-0.080**	(0.031)
turnout x 22apr2020	-0.052*	(0.031)	-0.077**	(0.031)
turnout x 23apr2020	-0.050	(0.031)	-0.074**	(0.031)
turnout x 24apr2020	-0.046	(0.031)	-0.070**	(0.031)
turnout x 25apr2020	-0.047	(0.031)	-0.071**	(0.031)
turnout x 26apr2020	-0.049	(0.031)	-0.073**	(0.032)
turnout x 27apr2020	-0.059*	(0.032)	-0.084***	(0.032)
turnout x 28apr2020	-0.063**	(0.032)	-0.087***	(0.032)
turnout x 29apr2020	-0.069**	(0.032)	-0.094***	(0.032)
turnout x 30apr2020	-0.064**	(0.032)	-0.089***	(0.032)
turnout x 01may2020	-0.068**	(0.032)	-0.095***	(0.032)
turnout x 02may2020	-0.077**	(0.032)	-0.105***	(0.032)
turnout x 03may2020	-0.077**	(0.032)	-0.103***	(0.032)
turnout x 04may2020	-0.077**	(0.032)	-0.104***	(0.032)
turnout x 05may2020	-0.080**	(0.032)	-0.105***	(0.032)
turnout x 06may2020	-0.084***	(0.032)	-0.110***	(0.033)
turnout x 07may2020	-0.086***	(0.032)	-0.110***	(0.032)
turnout x 08may2020	-0.080**	(0.033)	-0.106***	(0.033)
turnout x 09may2020	-0.077**	(0.032)	-0.104***	(0.032)
turnout x 10may2020	-0.075**	(0.033)	-0.102***	(0.033)
turnout x 11may2020	-0.083**	(0.033)	-0.109***	(0.033)
turnout x 12may2020	-0.077**	(0.033)	-0.101***	(0.033)
turnout x 13may2020	-0.071**	(0.033)	-0.097***	(0.033)
turnout x 14may2020	-0.077**	(0.033)	-0.104***	(0.033)
turnout x 15may2020	-0.080**	(0.032)	-0.106***	(0.032)
turnout x 16may2020	-0.080**	(0.032)	-0.105***	(0.032)
turnout x 17may2020	-0.087***	(0.032)	-0.111***	(0.032)
turnout x 18may2020	-0.078**	(0.032)	-0.102***	(0.033)
turnout x 19may2020	-0.078**	(0.032)	-0.102***	(0.032)
turnout x 20may2020	-0.082**	(0.032)	-0.106***	(0.032)
turnout x 21may2020	-0.071**	(0.032)	-0.096***	(0.032)
turnout x 22may2020	-0.065**	(0.032)	-0.091***	(0.033)
turnout x 23may2020	-0.065**	(0.032)	-0.091***	(0.032)
turnout x 24may2020	-0.063**	(0.032)	-0.090***	(0.032)
turnout x 25may2020	-0.063*	(0.033)	-0.089***	(0.033)
turnout x 26may2020	-0.067**	(0.032)	-0.092***	(0.032)
turnout x 27may2020	-0.070**	(0.032)	-0.096***	(0.032)
turnout x 28may2020	-0.076**	(0.032)	-0.101***	(0.032)
turnout x 29may2020	-0.085***	(0.032)	-0.111***	(0.033)
turnout x 30may2020	-0.090***	(0.033)	-0.117***	(0.033)

continued

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Table C.5 continued

	(1)		(2)	
turnout x 31may2020	-0.084**	(0.033)	-0.111***	(0.033)
turnout x 01jun2020	-0.089***	(0.033)	-0.115***	(0.033)
turnout x 02jun2020	-0.090***	(0.033)	-0.119***	(0.033)
turnout x 03jun2020	-0.088***	(0.033)	-0.118***	(0.033)
turnout x 04jun2020	-0.091***	(0.033)	-0.120***	(0.033)
turnout x 05jun2020	-0.091***	(0.033)	-0.119***	(0.033)
turnout x 06jun2020	-0.084**	(0.033)	-0.113***	(0.033)
turnout x 07jun2020	-0.082**	(0.033)	-0.111***	(0.033)
turnout x 08jun2020	-0.077**	(0.033)	-0.106***	(0.034)
turnout x 09jun2020	-0.081**	(0.033)	-0.110***	(0.034)
turnout x 10jun2020	-0.082**	(0.033)	-0.111***	(0.033)
turnout x 11jun2020	-0.079**	(0.033)	-0.108***	(0.033)
turnout x 12jun2020	-0.080**	(0.033)	-0.109***	(0.033)
turnout x 13jun2020	-0.081**	(0.033)	-0.109***	(0.033)
turnout x 14jun2020	-0.080**	(0.033)	-0.110***	(0.034)
turnout x 15jun2020	-0.077**	(0.033)	-0.107***	(0.034)
turnout x 16jun2020	-0.061*	(0.033)	-0.088***	(0.033)
turnout x 17jun2020	-0.063*	(0.033)	-0.090***	(0.033)
turnout x 18jun2020	-0.071**	(0.033)	-0.097***	(0.033)
turnout x 19jun2020	-0.078**	(0.033)	-0.105***	(0.033)
turnout x 20jun2020	-0.078**	(0.033)	-0.105***	(0.033)
turnout x 21jun2020	-0.071**	(0.033)	-0.098***	(0.033)
turnout x 22jun2020	-0.075**	(0.033)	-0.106***	(0.033)
turnout x 23jun2020	-0.066**	(0.033)	-0.097***	(0.033)
turnout x 24jun2020	-0.058*	(0.033)	-0.090***	(0.034)
turnout x 25jun2020	-0.048	(0.034)	-0.079**	(0.034)
turnout x 26jun2020	-0.057*	(0.034)	-0.088**	(0.034)
turnout x 27jun2020	-0.071**	(0.034)	-0.099***	(0.034)
turnout x 28jun2020	-0.070**	(0.034)	-0.099***	(0.034)
turnout x 29jun2020	-0.073**	(0.034)	-0.105***	(0.034)
turnout x 30jun2020	-0.063*	(0.034)	-0.095***	(0.034)
municipality FE	yes		yes	
NUTS3 x day FE	yes		yes	
controls x day FE	no		yes	
mean	4.653		4.653	
observations	592,128		592,128	

Panel B − Netherlands

	(1)		(2)	
turnout x feb week 1	-0.053	(0.080)	-0.129	(0.091)
turnout x feb week 2	-0.042	(0.072)	-0.067	(0.077)
turnout x feb week 4	-0.033	(0.066)	-0.118	(0.078)
turnout x mar week 1	-0.028	(0.080)	-0.064	(0.093)
turnout x mar week 2	-0.060	(0.096)	-0.185*	(0.108)
turnout x mar week 3	-0.059	(0.086)	-0.092	(0.099)
turnout x mar week 4	-0.071	(0.092)	-0.104	(0.100)
turnout x apr week 1	-0.157*	(0.092)	-0.187*	(0.102)
turnout x apr week 2	-0.155*	(0.090)	-0.186*	(0.101)
turnout x apr week 3	-0.174*	(0.092)	-0.205*	(0.105)
turnout x apr week 4	-0.177**	(0.086)	-0.187**	(0.094)
turnout x may week 1	-0.215**	(0.087)	-0.190**	(0.096)
turnout x may week 2	-0.207**	(0.085)	-0.178*	(0.094)
turnout x may week 3	-0.249***	(0.088)	-0.209**	(0.095)
turnout x may week 4	-0.279***	(0.089)	-0.234**	(0.102)
turnout x jun week 1	-0.229***	(0.086)	-0.210**	(0.097)
turnout x jun week 2	-0.202**	(0.086)	-0.172*	(0.099)
turnout x jun week 3	-0.164*	(0.090)	-0.210**	(0.099)
turnout x jun week 4	-0.227**	(0.089)	-0.173*	(0.098)
controls x week FE	no		yes	
municipality FE	yes		yes	
NUTS3 x week FE	yes		yes	
mean	3.756		3.756	
observations	4,969		4,969	

Panel C − Great Britain

	(1)		(2)	
turnout x feb week 1	-0.150	(0.136)	-0.362*	(0.213)
turnout x feb week 2	-0.190	(0.167)	-0.097	(0.234)
turnout x feb week 3	-0.354**	(0.139)	-0.249	(0.219)
turnout x mar week 1	0.025	(0.163)	-0.252	(0.261)
turnout x mar week 2	0.014	(0.137)	-0.198	(0.196)
turnout x mar week 3	-0.311	(0.313)	-0.360	(0.228)
turnout x mar week 4	-0.391	(0.287)	-0.518	(0.335)
turnout x apr week 1	-0.273**	(0.136)	-0.484**	(0.212)
turnout x apr week 2	-0.288**	(0.134)	-0.454**	(0.227)
turnout x apr week 3	-0.305**	(0.127)	-0.458**	(0.208)
turnout x apr week 4	-0.309**	(0.123)	-0.460**	(0.202)
turnout x may week 1	-0.318***	(0.121)	-0.442**	(0.200)

Table C.5 continued

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

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