Real-time tracking of the economic impact of COVID-19: insights from the first wave of the pandemic across Europe

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Abstract

This paper develops a methodology for tracking in real time the impact of the COVID-19 pandemic on economic activity by analyzing high-frequency electricity market data. The approach is validated by several robustness tests and by contrasting our estimates with the official statistics on the recession caused by COVID-19 in different European countries during the first two quarters of 2020. Compared with the standard indicators, our results are much more chronologically disaggregated and up-to-date and, therefore, can inform the current debate on the appropriate policy response to the pandemic. Unsurprisingly, we find that nations that experienced the most severe initial outbreaks also grappled with the hardest economic recessions. However, we detect diffused signs of recovery, with economic activity in most European countries returning to its pre-pandemic level by August 2020. Furthermore, we show how delaying intervention or pursuing “herd immunity” are not successful strategies, since they increase both economic disruption and mortality. The most effective short-run strategy to minimize the impact of the pandemic appears to be the introduction of early and relatively less stringent non-pharmaceutical interventions.

Keywords: COVID-19 | lockdown | economic impact | mortality | GDP | electricity demand | high frequency | real time indicators | fixed effects

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Introduction

In order to mitigate the spread of COVID-19 infections, governments across the world have introduced a variety of non-pharmaceutical interventions (NPIs), including social-distancing, mass testing, mobility restrictions, lockdowns, school closures and businesses shut-downs (1). Given the absence of a vaccine or a treatment, these restrictive policies saved lives by reducing the contagion and by alleviating the burden on health care systems (2-5). However, they have also generated remarkable economic and social disruption. At the time of writing this manuscript, in August 2020, the European Union (EU) is gradually reopening its economy after weathering the pandemic’s first wave, while the virus is still spreading fast in the Americas, Africa and Asia. At the same time, the crucial debate on the extent of the costs and benefits of NPIs and the existing trade-offs between slowing the pace of the pandemic (i.e. “flattening the curve”) and reducing financial impacts is rampant in both the academic and policy arenas (3–8).

Such discussion needs to be informed by timely evidence on the state of the economy and the impacts of the pandemic. Unfortunately, official macroeconomic indicators are insufficient for this task, since they are published with a typical 2-3 months delay and with relatively slow frequency. This creates a substantial window of uncertainty for policy design and evaluation. For this reason, researchers have proposed alternative, high-frequency proxies to track, in almost real-time, economic activity. Such indicators provide invaluable information for short-term assessment. The most promising measures include consumers’ transactions (9–11), mobility (12, 13), nitrogen oxide emissions (13, 14), electricity consumption (13, 15, 16) or mixtures of different indicators (17). Each of these variables has advantages and disadvantages. This paper focuses on electricity consumption. Electricity use does not come with the highly detailed geographical resolution of some of the other indicators (12, 14, 17), but has two main advantages. First, it is arguably the one that correlates the most with the Gross Domestic Product (GDP), since all economic activities require electricity as an input that is difficult to substitute away from, at least in the short-run. Second, it is easily accessible in real-time for most countries across the globe and, therefore, it is widely applicable for cross-country comparisons.
Several studies interpreted the current reduction in electricity consumption, which in the energy economics literature is often referred with the term “load”, as a signal of economic recession (13, 15, 16). However, correct inference on the impact of the pandemic requires taking into account all drivers of electricity consumption, both in the long- (e.g. technological change) and in the short-run (e.g. temperature, weekly seasonality), so that the estimated effects are not biased by any omitted factors. From this perspective, there is not yet an agreement on the appropriate methodology. Some studies use as counterfactual (i.e. the value of electricity consumption had the pandemic not occurred) the value of load in the same days of the previous years (18, 19), while others employ forecasting models (20, 21) or fixed-effect approaches (13, 15, 16, 22, 23). Unfortunately, without any formal testing, it is impossible to evaluate the correctness of all the different approaches proposed so far. Another gap in this newborn literature is the lack of a systematic and validated approach to rescale electricity load changes into GDP impacts.

Given this background, the first contribution of this manuscript is to develop a generalized methodology to measure short-run GDP impacts from daily electricity data. A fundamental novelty of our approach is that it comes with two companion time-placebo tests to ensure that our estimates are not biased by any unobserved factors and, therefore, can be interpreted as the economic impact of the pandemic. Furthermore, unlike previous papers, we validate our approach by comparing our GDP estimates against the available official statistics. We find an almost perfect 1:1 correspondence, with an impressive correlation coefficient of 0.98. This result demonstrates the reliability of our methodology for assessing the economic effect of the pandemic in real-time.

The second contribution of this paper is the empirical investigation of the economic impacts of the first wave of COVID-19 across Europe. We select 12 European countries representing the heterogeneous development of the pandemic across the entire continent, in terms of both severity of the outbreak and strength and timing of NPIs implementation. This comparison informs the debate on the appropriate policy response to COVID-19. In brief, we find that nations that experienced the most severe initial outbreaks (e.g. Italy, Spain) also grappled with the hardest economic recessions. However, our most recent estimates indicate widespread signs of recovery, revealing the temporary nature of this type of economic shock. We detect a sharp drop followed by a slow but steady recovery, consistent with a “U-shaped” shock (24). Furthermore, countries
that have introduced containment measures earlier in the course of the pandemic (e.g. Denmark, Norway) have experienced lower losses, partly because such measures were less stringent. The comparison of Sweden, the only EU country where no lockdown was implemented, with the other Scandinavian nations reveals that the Swedish economy is currently faring significantly worse than those of its neighbors. Therefore, it is simplistic to focus on NPIs such as lockdowns as the main cause of the recession. For example, supply-chain disruptions and consumers’ behavioral changes impact economic activity regardless of government policies (11). The implementation of early and relatively less stringent (or targeted) NPIs appears to minimize the economic impact of the pandemic and, at the same time, to save lives.

**The impact of the pandemic on electricity consumption**

We introduce our results by presenting some illustrative features of electricity consumption and, at the same time, provide a first, visual inspection of the impact of COVID-19. For this introduction we focus on Belgium, which was one of the European countries severely hit by the pandemic (the same results for each of the 12 countries in our analysis are reported in Section 1 of the Supplementary Information, S1). In panel A of Figure 1 we display daily electricity consumption data. Observing the gray line, which represents load in the first 9 months of 2019, we notice all the peculiar characteristics of electricity demand, such as the pronounced weekly seasonality (the reduced business activity in the weekends translate into roughly a 20% drop in load) and the smoother, annual seasonality, which follows the path of temperature, with peaks in winter when heating demand is at the highest. Electricity load in 2020, shown by the black line, follows similar patterns. Focusing only on the data before the lockdown, however, we notice how the overall level of consumption is somewhat lower than in 2019. This gap can be explained by differences in air temperature and/or by the long-run evolution of electricity demand, which, in turn, is affected by a variety of factors including economic growth and technological innovation. However, the difference between the two series increases significantly around the middle of March, when NPIs were introduced to curb the spread of infections. The gap is at its widest during the month of April, when the most restrictive measures were in place, and then gradually reduces with the steady re-opening of the economy in the following weeks.
In panel B, we observe the same time series after they have been pre-filtered in order to adjust for differences in temperature, holidays, weekly seasonality and long-run evolutions of demand (see Material and Methods, MMs). Now the yearly seasonality is less evident, and two series are much closer to each other during the pre-lockdown period, which we interpret as a sign that our pre-filtering approach functions well. In line with the un-adjusted time series, also in this panel we notice the clear reduction in electricity consumption during the lockdown weeks. The gap between the two series diminishes alongside the gradual easing of the restrictions. During the first half of August, in fact, the 2020 consumption is actually above the 2019 one.

Panel C shows the estimated weekly impact of the pandemic on electricity consumption, which we model as a series of fixed-effects parameters (details are in MMs). We do not restrict the parameters before the outbreak to be zero but, rather, include them in the model to serve as the first in-time placebo tests for our results. Since all the effects before the lockdown are non-significant, we find no rationale to doubt that our model is able to capture all the peculiar dynamics of load. We also run a second in-time placebo test, by applying the same approach to all 52 weeks of 2019, which our model also passes (details in MMs and results for all countries in S2.1). These two tests reassure us on the interpretability of the coefficients after the outbreak as the impact of COVID-19. Regarding such impacts, we estimate a strong and significant reduction in electricity consumption, varying between -15% and -10% during the weeks of strictest policies. The loosening of the restrictions, which started after the first week of May, prompted a gradual resumption of electricity demand. In the last four weeks of our sample (August 2020) electricity consumption is not significantly different from what it would have been had the pandemic not occurred. Therefore, our findings indicate that the Belgian economy has returned to normality.

**From electricity consumption to economic activity**

After estimating the effect of COVID-19 on electricity consumption, we derive implied GDP impacts (see MMs). Figure 2 validates our approach by comparing our estimates with the official and publicly available GDP changes. At the time of writing this manuscript, this information is
available for all the countries in our sample for only the 1st and 2nd quarter of 2020, with some estimates still being marked as “provisional”. Figure 2 shows how our results are remarkably close to the impacts derived from the official statistics. Excluding the provisional values, which we represent with a gray color, the correlation between the two estimates is 0.98 (it drops to 0.95 after including also the provisional values) and most points are along the 45° line. This comparison confirms the validity of our method for inferring GDP changes from electricity data.

[ Figure 2 about here ]

Of course, our estimates are considerably more chronologically disaggregated and up-to-date than the official statistics and, therefore, allow us to monitor in real-time the impact of the pandemic. Furthermore, our weekly results provide disaggregated information on the evolution of economic activity which is hidden in the quarterly statistics. Figure 3 illustrates such findings in detail, focusing on four countries. We attempt to represent concisely the whole range of developments of the pandemic across Europe, taking into account both the severity of the outbreak and the strength of governments’ reactions (results for all countries are in S3). The top-left panel illustrates our estimates for Belgium. We observe an initial steep decline and a gradual path of return to normalcy. This latter pattern is very encouraging, but it is lost if we only look at the official, quarterly information, again highlighting the value of our approach. As shown in S3, all countries that have experienced early COVID-19 outbreaks and introduced swift and strict lockdown policies (e.g. France, Italy, Spain) show similar dynamics.

[ Figure 3 about here ]

In the top-right corner we represent the impact for Great Britain (GB). GB also experienced a rapid increase in COVID-19 cases, but somewhat delayed intervention. In this respect, the speech of the British Prime Minister on the 11th of March 2020 was emblematic when he warned the public to “lose loved ones before their time”\(^4\). Eventually, the number of infections skyrocketed and also Britain adopted strict lockdown policies, enacted from the 26th of March 2020. This delay

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\(^4\) Prime Minister's statement on coronavirus (COVID-19): 12 March 2020, accessible at: https://www.gov.uk/government/speeches/pm-statement-on-coronavirus-12-march-2020
was likely one of the causes of longer British lockdown, at least compared to other European countries (British residents were under lockdown for 12 weeks while, for example, in Belgium and Italy such restrictions lasted only 8 weeks). Our estimates highlight the steep economic impact of COVID-19, which appears to have reduced British GDP between 20% and 30% during the lockdown. Fortunately, we start observing signs of recovery in August 2020.

On the bottom panels we represent two countries that in March 2020 were experiencing much lower number of COVID-19 cases per capita and, therefore, had more time to prepare their policy response to the pandemic: Denmark and Sweden. Most countries in Northern and Eastern Europe had similar initially low number of cases. The two countries represented here dealt with COVID-19 following two very different approaches. Denmark acted quickly and imposed a relatively “light” lockdown, e.g. closing schools, large shopping centers and urging people to work from home. Sweden, on the other hand, preferred to not enforce any significant restrictions, allowing shops, restaurants and most schools to remain open, and simply encouraged social-distancing behavior, relying on individual responsibility to curtail the spread of the virus (11, 25). According to our estimates, during the lockdown period Denmark experienced a limited reduction in economic activity, roughly between 5% and 10% (while on a weekly basis some effects are non-significant, when aggregated to the monthly level they all become significant, see S3), which quickly recovered after the loosening of the restrictions. On the other hand, for Sweden we do not detect any significant GDP reduction until the last two weeks of April 2020. However, by the beginning of May we estimate a clear and significant drop, which disappears only at the very tail end of our data.

These findings reveal that not implementing any lockdown does not shelter a country from the adverse economic impacts of COVID-19. Lockdowns can have, of course, significant short-term effects on GDP, as the estimates for Belgium and Britain demonstrate. However, the Swedish experience indicates that identifying national policies as the sole culprit of economic recession is simplistic. Countries do not exist in isolation, and spillover effects have significant repercussions for both real and financial markets (26). On the production side, for example, the disruption of global supply chains can have tremendous consequences, especially in the manufacturing sector, and the general climate of uncertainty generated by the pandemic can depress both financial
markets and investments (27). On the demand side, the risk of contracting the virus can reduce consumption, in particular among the more at-risk individuals (11).

**Comparing economic impacts and health outcomes across countries**

Figure 4 combines our estimated economic impacts with mortality information, in order to contribute to the debate on the existing trade-offs between financial and public health costs. We do not rely on the official infection and mortality rates statistics, since differences in national reporting methods invalidate cross-country comparisons (3). Instead, we identify the impact of the pandemic by comparing excess deaths in 2020 with the average of the same period in the previous five years (3, 28, 29). On the horizontal axis we present the cumulated excess deaths per 100,000 residents until the first week of April 2020. Considering that the development of COVID-19 infections (including incubation) is about 3-4 weeks, this measure is a proxy for the rate of infected individuals in the first week of March 2020, i.e. roughly the time in which COVID-19 was declared a pandemic by the World Health Organization (30). This is when European governments realized the severity of the problem and started considering introducing widespreads NPIs. In other words, it represents the exposure of each country to COVID-19 a priori of any significant national-level policy intervention. At the higher end, we find Italy and Spain, where the pandemic developed the earliest, while, at the lower end, we observe the Scandinavian countries, which had a more fortunate outset. On the vertical axis we present the overall mortality rate of the pandemic so far. Not surprisingly, there is a strong and positive relation between the two measures, represented by the dashed line: the countries most exposed to the initial outset of the pandemic are also those recording the highest total number of deaths per capita. On the other hand of the spectrum, countries that introduced NPIs earlier in the course of the pandemic experienced lower mortality rates. Economic impacts (represented by the size of the bubbles) indicate a similar trend, with the most exposed countries facing the hardest losses.

[ Figure 4 about here ]

This generalized relationship presents two obvious outliers: Sweden and Britain, the only two countries that did not enforce lockdowns as soon as infections became widespread in Europe and,
at least initially, tried to pursue a “herd immunity” strategy (25, 31). Consistent with previous findings (2, 11, 25, 32, 33), our graph suggests that the light-touch approach of the Swedish government produced a much higher death rate than the one experienced by the other Scandinavian countries (despite the comparable health systems) without generating any economic benefit. Britain’s initial “keep calm and carry on” strategy and the late decision to pursue a lockdown seem to have created analogous consequences, with GB currently being the country with both the highest mortality rate and the most significant economic recession, despite experiencing an initial COVID-19 exposure close to the average level and comparable, for example, with that of France and the Netherlands. When interpreting these results we need to keep in mind that both the economic and public health impacts of the pandemic are driven by the complex interactions of several different factors, such as population density (34), behavior (35), weather (36), age (37), health system (38) and the structure of the economy (27), which, in turn, do not allow us to draw precise counterfactual predictions on specific policies. However, it is highly unlikely that at least a significant fraction of the gap between the general European trend and the two “outlier countries” is not a direct consequence of their unconventional policy choices.

Conclusions

This work demonstrated that widely available electricity consumption data can be used to track in real-time the economic impact of the current pandemic. We developed a new methodology that also includes two companion time-placebo tests, which are fundamental to ensure that estimates are not affected by omitted variable bias and, therefore, can be interpreted as causal impacts. We established a simple and yet effective strategy to translate electricity consumption changes into GDP implications, which we validated against official estimates. Since such official indicators are only available with a certain delay and in aggregate form, the timeliness provided by our approach is essential for short-term policy assessment. Our methodology is not limited to the study of COVID-19, but it is applicable to monitor the impact of other types of crises, including financial depressions and natural disasters (39). However, an important caveat is that it is only valid to assess short-run impacts. In the long-run, in fact, potential demand responses to price changes and technological innovation may affect our estimates. Nevertheless, such factors are, most likely, not significant over the time horizon in which official indicators are unavailable. Another caveat is that
our estimates should be interpreted as the overall impact of the COVID-19 pandemic, rather than being tied-up to specific national policies, because of the potential confounding effect of behavioral changes (11, 35) and international spillovers (26).

Our comparison of the first wave of COVID-19 across different European countries needs to fully acknowledge the substantial differences characterizing their health, social and economic systems, which in turn can greatly affect both the financial and public health impacts of the pandemic (27, 34–38). While being fully aware of such heterogeneity, we can still rely on the different timing and intensity of the initial COVID-19 outbreak and related policy responses to draw meaningful conclusions. First, the nations that weathered the strongest and earliest outbreaks (e.g. Italy, Spain) typically implemented the strictest NPIs and experienced the sharpest economic recessions. Nevertheless, in August 2020 we begin to observe widespread signs of recovery, with the GDPs of most countries returning to their pre-outbreak levels, consistent with a U-shaped economic shock (24). Second, delaying intervention or pursuing “herd immunity” do not appear to be successful strategies. The two countries that followed such approaches (respectively Britain and Sweden) performed remarkably worse than all the other nations that experienced a similar initial exposure to the pandemic, both in terms of financial and mortality outcomes. Therefore, not implementing any lockdown does not protect a country from the current economic recession, whose causes are more profound, and reside in both supply (e.g. international spillovers) and demand (e.g. behavioral changes) shocks.

Expecting a clear trade-off between saving lives and maintaining economic activity creates a false dichotomy, since these two goals are inextricably related to each other. The most effective short-run strategy to minimize the economic impact of the pandemic and, at the same time, reduce the spread of the infection, appears to be the introduction of early and relatively less stringent (or targeted) NPIs, which can then quickly be relaxed when infection rates return under control. These conclusions, however, come with a few important caveats. NPIs impose significant restrictions on individual rights and freedom (40), have wide social and psychological impacts (41, 42), promote an increase in inequalities (12, 43, 44) and may present other long-run consequences such as impacts on human capital which, at the moment, are very difficult to forecast. Our estimates do not take into account any of these issues.
Material and methods

Data and software. We derive day-ahead electricity market data from the information reported by the European Network of Transmission System Operators for Electricity (ENTSO-E) for the period between 01-01-2015 and 26-08-2020. Daily weather data is retrieved from the University of Dayton archive and the monitoring stations of the National Oceanic and Atmospheric Administration and Weather Underground, depending on availability. Official statistics on GDP growth are available from the Organization for Economic Co-operation and Development and from national institutes of statistics. Country-level data on the share of electricity consumption of the residential sector is provided by the International Energy Agency (IEA). Data on excess deaths comes from the European Monitoring of Excess Mortality for Public Health Action (EuroMOMO) and The Economist. We derive information on holidays and NPIs implementations from different online sources. We run our analyses in R (45). For a detailed description of all the data sources and the R packages see S5.

Modeling approach. Our approach generalizes the fixed-effects estimator already implemented to measure the impact of the pandemic by comparing electricity consumption in 2020 against previous years (15, 16, 22). Our main methodological novelties are 1) the pre-filtering approach (46), developed to remove the short- and long-run drivers of electricity demand (such as technological innovation and economic development), 2) the two time-placebo tests, xxx that our estimates are not affected by omitted variable bias and 3) the validation of our GDP impact estimates against official statistics. Finally, we run our analysis after eliminating all weekends from the data. This choice reduces the weekly seasonality and allows us to focus on the days in which most economic activities are carried on (however, it does not affect our results, as show in the robustness tests below). The different steps of our approach, which we repeat separately for each country, are detailed as follows.

Pre-filtering: After removing the weekends, we pre-filter electricity load data following a two-steps approach. In the first step, we control for the impact of temperature, holidays and weekly seasonality. Using only the data before the outbreak, i.e. from 01/01/2015 to 03/03/2020 (the latter
date is about a week before the start of the lockdown in Italy, the first country in Europe to experience the outbreak), we estimate the following model:

\[
y_t = \delta_0 + \delta_1 \text{temp}_t + \delta_2 (\text{temp}_t - k) d_{kt} + \sum_{w=1}^4 \beta_w d_{wt} + \sum_{w=1}^6 \beta_h d_{ht} + e_t,
\]

where \( y_t \) is the natural logarithm of electricity load in day \( t \), \( \text{temp}_t \) is the mean daily air temperature, \( k \) is the threshold at which the relationship between electricity demand and temperature reverts, \( d_{kt} \) is a dummy variable equal to 1 if \( \text{temp}_t > k \) and equal to 0 otherwise, \( d_{wt} \) are four dummy variables identifying the day of the week (with Monday as baseline), \( d_{ht} \) are six dummy variables identifying six different types of public holidays effects (generic public holidays, gap day between a holiday and a Sunday, gap day between a holiday and a Saturday, Christmas, New Year’s Day, 31st of December) and \( e_t \) is the error component. We chose \( k \) by visually inspecting the data in each country (typically 60°F). After estimating this model via Ordinary Least Squares (OLS) we obtain adjusted electricity load as: \( \hat{y}_t = y_t - \hat{y}_t \), where the “hat” accent indicates the prediction from equation (1). This measure of electricity load can be thought as the fraction of consumption independent from temperature, weekly seasonality and holidays. In the second step of our pre-filtering approach we control for the energy efficiency and the general level of economic activity in different years by estimating yearly fixed effects. Such fixed effects cannot be estimated on the entire dataset, since the fixed effect for year 2020 would capture also the average impact of the pandemic. Therefore, for each year we consider only the data corresponding to the period before the outbreak, i.e. from the 01/01 to the 03/03 (this corresponds to 56 days in each year for a total of 336 observations) and specify the following model:

\[
\hat{y}_t = \alpha_0 + \sum_{i=1}^5 \alpha_i d_i + v_t,
\]

where \( d_i \) are 5 dummy variables for the years 2015-2019 (with 2020 as the base year), \( v_t \) is the error component and \( \alpha_0, ..., \alpha_5 \) are the fixed-effect parameters that we estimate via OLS. We then subtract to \( \hat{y}_t \) the appropriate fixed effect in each year, obtaining our electricity load time series adjusted for temperature, weekly seasonality, holidays and yearly fixed-effects, which we indicate with \( \hat{y}_t \). This is the dependent variable in the rest of our analysis.
Electricity load modeling. We employ two different types of fixed effects in order to capture the remaining features of electricity consumption dynamics and, therefore, to isolate the causal impact of COVID-19. The model can be written as:

\[ \hat{y}_t = \beta_0 + \gamma_t + \gamma_{t,2020}^* + u_t, \]

where \( \hat{y}_t \) is the natural logarithm of electricity load after the two-steps pre-filtering process, \( \gamma_t \) are week-of-the-year fixed effects, \( \gamma_{t,2020}^* \) are week-of-the-year fixed effects interacted with a dummy variable identifying year 2020, and \( u_t \) is the random component, which we specify as an autoregressive model of order one, AR(1), to capture residual autocorrelation (16). The resulting specification can be estimated via maximum likelihood. The week-of-the-year fixed effects \( \gamma_t \) encompass the slow-moving yearly seasonality connected to the remaining effect of weather, daylight hours and cultural habits, such as the reduction in economic activity during the summer and winter. The coefficients of interests are the \( \gamma_{t,2020}^* \): they measure the differences in electricity consumption between each week of year 2020 and the average of the corresponding week in the previous five years which cannot be explained by any of the other observed factors. We expect these coefficients to be negative and significant when the NPIs and the general crisis generated by the pandemic start affecting economic activities. On the other hand, if the model is correctly specified, the \( \gamma_{w,2020}^* \) coefficients corresponding to the weeks before the outbreak should be not significantly different from zero. This consideration allows us to design two in-time placebo tests. To carry out the first one, we simply include in the model the \( \gamma_{w,2020}^* \) corresponding to the weeks before the outbreak. If our approach is successful in capturing all the peculiar features of electricity consumption, these parameters should be non-significantly different from zero. In the second test we eliminate year 2020 and run the entire analysis as if the pandemic happened in year 2019. Again, in order to pass this test, the weekly effects corresponding to year 2019 should be non-significantly different from zero. We report these results in S2.1. Lastly, similarly to (13, 15, 16, 22, 23), this model does not include any electricity price effect, since short-run electricity demand elasticity can be considered as perfectly inelastic (47, 48).

Electricity load impact estimation. In order to estimate the impact of the pandemic on electricity consumption we compare daily in-sample predictions for year 2020 obtained by a) the full model
in Eq. 3 and \(b\) the same model in which all the \(\gamma_{w,2020}\) parameters are set to zero. While the former predictions represent our best-fitting estimates, the second one corresponds to the value that, according to our model, electricity consumption would have had if the pandemic had not happened, i.e. if the pattern of pre-filtered electricity consumption would have followed the same dynamics of the previous years. Indicating these two predictions (on the original scale of the variable) respectively with \(\hat{Y}_t\) and \(\hat{Y}_t^*\), we can write the percentage impact of COVID-19 on electricity load as:

\[
(4) \quad l_t = 100(\hat{Y}_t - \hat{Y}_t^*) / \hat{Y}_t^* ,
\]

and derive appropriate confidence intervals running 5000 Monte Carlo simulations from the estimated joint distribution of the model’s parameters.\(^5\)

**Economic impact estimation.** Following findings in the recent literature (13, 15, 16) and our analysis of the electricity consumption reduction associated to the financial crisis of the years 2008-09 (see S4), we employ some deliberately simple assumptions to transform our estimates of electricity load changes into economic impacts. We assume that, in each country, GDP changes are proportional to the changes in electricity consumption by all productive sectors, i.e. all sectors but the residential one. Therefore, we rescale our estimates in Eq. 4, which are calculated on total electricity consumption, as follows. During regular days (i.e. no lockdown) we simply assume that residential consumption has remained unaffected and, therefore, all the reduction in electricity load due to the pandemic can be traced back to the other sectors. The resulting impact on GDP corresponds to: \(GDP_{nl,t} = l_t 100 / (100 - r)\), where \(r\) represents the percentage of consumption of the residential sector for the relevant country. During lockdown days, we follow IEA estimates (49) reporting that residential consumption has increased by 40% when such restrictions were in place, and rescale our calculations accordingly: \(GDP_{l,t} = l_t 100 / (100 - 1.4r)\). The lockdown dates for each country are in S5.3. Figure 2 in the manuscript shows how our approach provides results that are remarkably close to the official estimates of the GDP changes during the first two quarters.

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\(^5\) Because of Jensen’s inequality, the prediction on the original variable scale are not simply the exponent of the prediction on the log, but actually depend on the distribution of the random component (50). Since, in our case, the difference is negligible because of the low noise-vs-signal ratio, for simplicity we employ the Gaussian distribution i.e. \(Y_t = \exp[y_t + (s^2/2)]\), with \(s\) indicating the estimated standard deviation of the error component.
of 2020. Importantly, the official indicators report GDP changes, and not the GDP impact of the pandemic. Therefore, for an appropriate comparison with our estimates, we need to subtract, from the official statistics, the GDP change that would have happened if the pandemic had not occurred. For simplicity we use assume this counterfactual to be the change in the corresponding quarter of 2019.⁶

**Robustness tests.** Apart from the two time-placebo tests illustrated previously, we also evaluate the robustness of our findings by 1) estimating the model using OLS, 2) analyzing all days including weekends and 3) focusing on peak time, i.e. daily data obtained aggregating only the hourly data from 8am to 6pm). Results remain stable in all these different specifications (S2.2).

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⁶ Alternative measures for this counterfactual could be the quarterly change of the last quarter of 2019 or the rescaled annual forecast for 2020 made in 2019 by the International Monetary Fund. Since, in the last few years, GDP growth has been relatively slow in all the countries considered in our study, using one measure or another does not affect our comparison.
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**FIGURES**

Figure 1: Electricity time series and COVID-19 impact for Belgium

Notes: plot A presents the original electricity consumption time-series, plot B presents the same time-series after prefiltering and plot C presents the estimated impacts of electricity consumption, with the vertical lines indicating 95% confidence intervals.
Figure 2: Relationship between our estimates and official statistics

Notes: Dots represent estimates for the 2020 Q1 and squares for 2020 Q2. In gray we plot estimates that are indicated as “provisional” in the OECD database. The correlation coefficient $\rho$ is calculated excluding these provisional data. Including such provisional data, it drops to 0.95.
Figure 3: Estimated impact of COVID-19 on GDP

Notes: The plots present weekly GDP impacts, with the vertical lines indicating the 95% confidence intervals. In different countries lockdowns were implemented and then gradually lifted following different strategies. To allow comparisons, here we indicate as “lockdown ends” the date in which all retail shops are reopened (dates for all countries are in S5.3).
Figure 4: Public health and economic impacts of COVID-19

Notes: Excess deaths calculated as the difference between the cumulated total deaths per 100,000 residents of each week of 2020 and the average cumulated deaths for the same week in the years 2015-2019. Week 14 corresponding to the first week of April and week 26 corresponding to the last week of June. The size of the balloons represents the overall GDP reduction estimated by our model until August 2020. Dashed line represent the best fitting local linear regression via non-parametric estimation.
Supplementary information for:

Real-time tracking of the economic impact of COVID-19: insights from the first wave of the pandemic across Europe

Carlo Fezzi\textsuperscript{7,8*} and Valeria Fanghella\textsuperscript{1,3}

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S1: Electricity time series plots and impacts

Here we replicate Figure 1 for all the countries included in our analysis. The top panel presents the original electricity consumption time-series, the middle panel presents the same time-series after prefiltering and the bottom panel presents the estimated impacts of electricity consumption, with the vertical lines indicating 95% confidence intervals.

S1.1 Austria

![Electricity consumption plots for Austria](image_url)
S1.2 Belgium

![Graphs showing load (Mw) and electricity impact (%) over months for Belgium in the years 2019 and 2020.]
S1.3 Denmark

![Graphs showing load and electricity impact over months for years 2019 and 2020]
S1.4 France
S1.5 Germany
S1.6 Great Britain
S1.7 Italy
S1.8 Netherlands
S1.9 Norway
S1.10 Spain
S1.11 Sweden

![Graphs showing load and log load (Mw) for years 2019 and 2020, as well as the electricity impact (%).](image)
S1.12 Switzerland
S2: Robustness tests

In this section we report the results from our robustness tests.

S2.1 In-time placebo tests

The two in-time placebo tests consist in evaluating the coefficients of the interaction term between year and weekly fixed-effects during time periods in which we do not have any reason to expect significant effects. In the in-time-placebo test 1, we test the significance of the coefficients of 2020 before the outbreak (weeks 1-8) and in the in-time-placebo test 2 we eliminate the data for 2020 and run the analysis for year 2019, i.e. we test the significance of all interaction effects between the weekly-fixed effect and a dummy for year 2019. In order to pass these two tests, all the coefficients should be non-significantly different from zero, with the exception of a few “false positives” compatible with type-I errors at the given significance level. Table S1 reports the results for all the countries in our analysis.

Table S1: In-time placebo tests

| Country     | In-time placebo 1 | In-time-placebo 2 |
|-------------|-------------------|-------------------|
|             | 5% | 10% | 5%  | 10% |
| Austria     | 0  | 0   | 0   | 1   |
| Belgium     | 0  | 0   | 3   | 5   |
| Denmark     | 1  | 1   | 0   | 1   |
| France      | 1  | 1   | 4   | 5   |
| Germany     | 0  | 0   | 18  | 23  |
| Italy       | 0  | 0   | 9   | 10  |
| Netherlands | 0  | 0   | 2   | 8   |
| Norway      | 0  | 0   | 3   | 6   |
| Spain       | 0  | 0   | 5   | 6   |
| Sweden      | 0  | 0   | 2   | 4   |
| Switzerland | 0  | 0   | 3   | 10  |
| United Kingdom | 0  | 0   | 1   | 2   |
| Average     | 0.2| 0.2 | 2.9 | 5.2 |
| Expected type I error | 0.5 | 0.9 | 2.6 | 5.2 |

Notes: the table reports number of tests failed in each country at each significance level. Average calculated by excluding Germany, expected type I error is the number of failed test compatible with the significance level.
All countries pass the first in-time placebo test with flying colors. Regarding the second test, all countries except Germany and, to a lesser extent, Italy, have a number of failed test compatible with the significance levels. After excluding Germany, the average number of failed tests is in line with the expected number of type-I errors (results reported in the last two rows). Despite Germany failing to pass this second test, our estimated GDP impacts are very close to the official indicators for the first two quarters of 2020 (see Figure 2 in the main paper), indicating that our misspecification is likely to be not very severe. Overall, the results for all other nations appears to be very robust. This analysis also shows how our tests perform well and are able to identify even small miss-specifications.

**S2.2 Alternative data definition and estimators**

In our main model we calculated daily electricity load by averaging all hourly (or intra-hourly) information of each day, we excluded weekends and estimated our model via maximum likelihood to allow the error term to have an AR(1) component. Here, we compare the estimated electricity load impacts in our main specification with three alternatives: 1) considering all days, including weekends, 2) estimating the main model with OLS, 3) focusing only on weekday peak hours, i.e. hours between 8am and 6pm,. In order to preserve space, we present results only for the four countries included in Figure 3, i.e. Belgium, Denmark, Great Britain and Sweden. In general, confidence intervals from considering all days are slightly smaller because the fixed effect parameters are estimated on 7 observations instead of 5. Also the OLS estimator generates smaller confidence intervals, since it does not take into account of any residual autocorrelation. Finally, using peak-only hours estimates a somewhat more intense reduction during the lockdown, since the peak represents the moment when working activities consume the highest percentage of electricity consumption. Despite these differences, the three alternative specification generate results that are consistent with those provided by our main model.
Figure S1: Alternative specifications for Belgium

Notes: the plots compare the estimated impact of COVID-19 on electricity consumption according to our base model and three alternative specifications: “all days” = including weekdays and weekends, “OLS” = estimating the model with OLS instead of ML, “peak only” = estimating the model using only peak hourly data, i.e. from 8am to 6pm). Vertical bars are 95% confidence intervals.
**Figure S2:** Alternative specifications for Great Britain

Notes: the plots compares the estimated impact of COVID-19 on electricity consumption according to our base model and three alternative specifications: “all days” = including weekdays and weekends, “OLS” = estimating the model with OLS instead of ML, “peak only” = estimating the model using only peak hourly data, i.e. from 8am to 6pm). Vertical bars are 95% confidence intervals.
Figure S3: Alternative specifications for Denmark

Notes: the plots compares the estimated impact of COVID-19 on electricity consumption according to our base model and three alternative specifications: “all days” = including weekdays and weekends, “OLS” = estimating the model with OLS instead of ML, “peak only” = estimating the model using only peak hourly data, i.e. from 8am to 6pm). Vertical bars are 95% confidence intervals.
**Figure S4**: Alternative specifications for Sweden

Notes: the plots compares the estimated impact of COVID-19 on electricity consumption according to our base model and three alternative specifications: “all days” = including weekdays and weekends, “OLS” = estimating the model with OLS instead of ML, “peak only” = estimating the model using only peak hourly data, i.e. from 8am to 6pm). Vertical bars are 95% confidence intervals.
S3: Estimated GDP impacts

Austria

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -9.29      | -12.36      | -6.17       | ***          |
| April | -16.27     | -19.5       | -13.07      | ***          |
| May   | -9.47      | -12.34      | -6.58       | ***          |
| June  | -13.01     | -15.78      | -10.2       | ***          |
| July  | -7.17      | -10.05      | -4.29       | ***          |
| August| -6.21      | -9.55       | -2.84       | ***          |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
Belgium

Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -8.53      | -11.44      | -5.55       | ***          |
| April | -16.53     | -19.42      | -13.63      | ***          |
| May   | -9.18      | -11.97      | -6.33       | ***          |
| June  | -4.52      | -7.33       | -1.55       | ***          |
| July  | -2.64      | -5.44       | 0.14        | *            |
| August| 0.99       | -2.4        | 4.31        |              |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
**Denmark**

### Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -5.73      | -10.56      | -0.91       | **           |
| April | -5.82      | -11.35      | -0.16       | **           |
| May   | -5.58      | -10.37      | -0.69       | **           |
| June  | -3.11      | -7.74       | 1.61        |              |
| July  | -2.85      | -7.29       | 1.64        |              |
| August| 0.41       | -4.8        | 6.02        |              |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

### Weekly GDP impacts plot

*Notes: vertical lines indicate 95% confidence intervals.*
### France

#### Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -12.91     | -19.54      | -6.31       | ***          |
| April | -26.1      | -33.45      | -19.16      | ***          |
| May   | -18.88     | -24.91      | -12.56      | ***          |
| June  | -15.48     | -21.04      | -9.58       | ***          |
| July  | -7.47      | -13.4       | -1.52       | **           |
| August| -1.52      | -8.52       | 5.8         |              |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

#### Weekly GDP impacts plot

*Notes: vertical lines indicate 95% confidence intervals.*
Germany

Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -6.53      | -9.29       | -3.66       | ***          |
| April | -15.33     | -18.06      | -12.53      | ***          |
| May   | -14.18     | -16.65      | -11.65      | ***          |
| June  | -12.11     | -14.56      | -9.62       | ***          |
| July  | -11.94     | -14.31      | -9.44       | ***          |
| August| -6.66      | -9.56       | -3.72       | ***          |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
Great Britain

### Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -5.3       | -10.38      | -0.36       | **           |
| April | -27.33     | -32.68      | -21.88      | ***          |
| May   | -21.28     | -26.63      | -15.64      | ***          |
| June  | -22.62     | -27.4       | -17.69      | ***          |
| July  | -22.38     | -26.53      | -18.31      | ***          |
| August| -8.04      | -13.22      | -2.79       | ***          |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

### Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
Italy

Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -18.73     | -22.04      | -15.19      | ***          |
| April | -30.25     | -33.42      | -27.01      | ***          |
| May   | -13.99     | -17.16      | -10.74      | ***          |
| June  | -11.42     | -14.65      | -8.18       | ***          |
| July  | -6.08      | -9.29       | -2.8        | ***          |
| August| 3.93       | -0.17       | 8.04        |              |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
Netherlands

Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -9.19      | -12.31      | -5.93       | ***          |
| April | -14.34     | -17.49      | -11.16      | ***          |
| May   | -14.01     | -16.99      | -10.95      | ***          |
| June  | -11.16     | -14.11      | -8.13       | ***          |
| July  | -9.04      | -11.93      | -6.2        | ***          |
| August| 2.29       | -1.35       | 5.97        |              |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
### Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -4.03      | -10.35      | 2.42        |              |
| April | -4.51      | -11.02      | 2.53        |              |
| May   | -8.38      | -13.76      | -2.75       | ***          |
| June  | -7.57      | -12.65      | -2.40       | ***          |
| July  | -8.81      | -13.87      | -3.57       | ***          |
| August| -3.60      | -9.43       | 2.38        |              |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

### Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
Spain

Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -8.17      | -11.41      | -4.86       | ***          |
| April | -25.9      | -29.00      | -22.55      | ***          |
| May   | -17.3      | -20.19      | -14.39      | ***          |
| June  | -11.5      | -14.28      | -8.84       | ***          |
| July  | -4.36      | -7.32       | -1.39       | **           |
| August| -1.35      | -4.72       | 2.05        |              |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
Sweden

Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -0.38      | -4.94       | 4.36        |              |
| April | -5.34      | -9.72       | -0.84       | **           |
| May   | -13.83     | -17.88      | -9.46       | ***          |
| June  | -7.73      | -12.03      | -3.41       | ***          |
| July  | -12.25     | -16.46      | -7.94       | ***          |
| August| -3.86      | -8.96       | 1.28        |              |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
Switzerland

Monthly GDP impacts

| Month | GDP impact | Lower bound | Upper bound | Significance |
|-------|------------|-------------|-------------|--------------|
| March | -7.00      | -12.5       | -1.27       | ***          |
| April | -13.16     | -19.24      | -6.87       | ***          |
| May   | -13.05     | -18.35      | -7.69       | ***          |
| June  | -14.00     | -18.58      | -9.24       | ***          |
| July  | -9.67      | -14.64      | -4.85       | ***          |
| August| -4.8       | -10.52      | 0.97        |              |

Notes: lower and upper bounds indicate 95% confidence intervals obtained with 5000 Monte Carlo repetitions. Stars indicate significance as follows: *** = 1%, ** = 5%, * = 10%.

Weekly GDP impacts plot

Notes: vertical lines indicate 95% confidence intervals.
S4: Electricity and GDP during the great recession

The sudden recession followed by a significant expansion in the years 2008-10 provides a great illustrative example for presenting the short-run relationship between electricity consumption and economic activity. Figure S5 reports the scatter plot between percentage change in electricity consumption and GDP between years 2008 and 2009 (the recession) and years 2009 and 2010 (the recovery) for the countries included in our main analysis, to which we also added United States, Canada, China, Russia and Australia in order to present a more complete picture. The relationship between the two variables is very strong, with a correlation coefficient of 0.91. Therefore, assuming a strong and linear short-run relation between electricity consumption and GDP is realistic and empirically grounded.

Figure S5: Relationship between GDP change and electricity consumption change

Notes: We report changes between years 2009-2008 and 2010-2009. Electricity consumption from IEA, GDP from World Bank. Data for the countries not included in our main analysis represented as squares. The value of $\rho$ indicates the correlation coefficient.
S5: Detailed data and software

In this section we report the detailed information on the data and software used in our analysis that, in order to preserve space, we omitted from the main manuscript.

S5.1 Data sources and preparation

Table S2: Detailed data sources

| Data             | Description                                                                 | Source                                                                                           | Web address                                      |
|------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|--------------------------------------------------|
| Electricity load | Hourly (or intra-hourly) day-ahead electricity consumption.                  | European Network of Transmission System Operators for Electricity (ENTSO-E)                       | [https://transparency.entsoe.eu/](https://transparency.entsoe.eu/) |
| Temperature      | For each nation we represent the overall profile of temperature by using as a proxy the daily average temperature in the country’s capital (the only exceptions are France / Bordeaux and Austria / Innsbruck because of data availability). The data is retrieved from the *University of Dayton weather archive*. Missing data are filled by collecting information for the same city from *NOAA* or *Weather Underground*, depending on availability. We control that temperature does not differ significantly across databases by running a linear regression on the overlapping data and accepting the alternative source only if the $R^2 > 0.85$. We then use the OLS coefficients to impute missing values. | University of Dayton National Oceanic and Atmospheric Administration (NOAA) Weather Underground | [http://academic.udayton.edu/kissock/http/Weather](http://academic.udayton.edu/kissock/http/Weather) [https://www.ncdc.noaa.gov/cdo-web/datatools](https://www.ncdc.noaa.gov/cdo-web/datatools) [https://www.wunderground.com/](https://www.wunderground.com/) |
| Share of residential load | Share of annual electricity load consumed by the residential sector in 2017. | International Energy Agency (IAE) | https://www.iea.org/data-and-statistics |
|--------------------------|---------------------------------------------------------------------|-----------------------------------|------------------------------------------|
| GDP changes              | GDP growth in the first and second quarter of 2020, relatively to the previous quarter. | Organization for Economic Cooperation and Development (OECD) | https://data.oecd.org/gdp/quarterly-gdp.htm |
| Excess deaths            | Weekly excess death for each country in year 2020 compared with the average 2015-2019 are retrieved from the open source database provided by The Economists, which download data from EuroMOMO. Excess deaths from Finland from Statistics Finland. | The Economist European Monitoring of Excess Mortality for Public Health Action (EuroMOMO) | https://github.com/TheEconomist/covid-19-excess-deaths-tracker |
|                          |                                                                      | Statistics Finland                | http://stat.fi/org/index_en.html         |
| Policies                 | Information on NPIs and lockdown                                    | Various online sources, for example (but not limited to) politico.eu | https://www.politico.eu/article/europe-coronavirus-post-lockdown-rules-compared-face-mask-travel/ |

**S5.2 Software information**

As explained in the manuscript, we run our entire analysis in R (1). We use the packages *lmtest* (2), MASS (3), *nlme* (4) and *sandwich* (5).

**S5.3 Lockdown dates**

Lockdown polices varied significantly across countries. Since our focus is the economic impact of the pandemic, in order to provide a comparable analysis between different nations, we define as
the data starting the lockdown date the one in which the first NPIs (school closure, mobility restrictions, etc.) were introduced, and the date ending the lockdown the one in which all retail shops are allowed to re-open.

**Table S3**: Lockdown dates used in our analysis

| Country   | Lockdown dates |
|-----------|----------------|
|           | start          | end            |
| Austria   | 16 March 2020  | 01 May 2020    |
| Belgium   | 18 March 2020  | 11 May 2020    |
| Denmark   | 18 March 2020  | 11 May 2020    |
| France    | 17 March 2020  | 11 May 2020    |
| Germany   | 17 March 2020  | 06 May 2020    |
| Great Britain | 26 March 2020  | 15 June 2020  |
| Italy     | 10 March 2020  | 04 May 2020    |
| Netherlands | 15 March 2020  | 11 May 2020    |
| Norway    | 12 March 2020  | 11 May 2020    |
| Spain     | 14 March 2020  | 11 May 2020    |
| Sweden    | --             | --             |
| Switzerland | 17 March 2020  | 11 May 2020    |

**References**

1. R Development Core Team, A language and environment for statistical computing (2006).
2. T. Hothorn, *et al.*, Package ‘lmtest’. (23 September 2020).
3. B. Ripley, *et al.*, Package ‘MASS’ (23 September 2020).
4. J. Pinheiro, *et al.*, Package ‘nlme’ (23 August 2020).
5. T. Lumley, A. Zeileis, Package ‘sandwich’ (24 September 2015).