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Tracking the Economic Impact of COVID-19 and Mitigation
Policies in Europe and the United States

by Sophia Chen, Deniz Igan, Nicola Pierri, and Andrea F. Presbitero

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I N T E R N A T I O N A L M O N E T A R Y F U N D

IMF Working Paper

Research Department

**Tracking the Economic Impact of COVID-19 and Mitigation Policies
in Europe and the United States**

Prepared by Sophia Chen, Deniz Igan, Nicola Pierri, and Andrea F. Presbitero¹

Authorized for distribution by Maria Soledad Martinez Peria

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Abstract

We use high-frequency indicators to analyze the economic impact of COVID-19 in Europe and the United States during the early phase of the pandemic. We document that European countries and U.S. states that experienced larger outbreaks also suffered larger economic losses. We also find that the heterogeneous impact of COVID-19 is mostly captured by observed changes in people's mobility, while, so far, there is no robust evidence supporting additional impact from the adoption of non-pharmaceutical interventions. The deterioration of economic conditions preceded the introduction of these policies and a gradual recovery also started before formal reopening, highlighting the importance of voluntary social distancing, communication, and trust-building measures.

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I. INTRODUCTION

As the COVID-19 pandemic spread across the globe, many countries adopted Non-Pharmaceutical Interventions (NPIs), such as school and business closures and shelter-in-place orders, to mitigate the outbreaks. NPIs are controversial due to uncertainty about their efficacy in containing the outbreak and potential negative economic effects (Correia, Luck, and Verner 2020; Lilley, Lilley, and Rinaldi 2020). Providing evidence of their effects is crucial in the reopening phase, where governments ponder lifting NPIs and restoring the economy to its normalcy. In fact, fine-tuning mitigation policies may greatly reduce the economic and human costs of the pandemic as shown by a fast-growing quantitative literature (see Acemoglu et al. 2020; Alvarez, Argente, and Lippi 2020; Favero, Ichino, and Rustichini 2020; Jones, Philippon, and Venkateswaran 2020, among others). Despite its urgency and importance, empirical evidence on mitigation policies is still scant.

Mandatory mitigation measures may exacerbate the economic impact of the pandemic, at least in the short run, by halting some activities, in particular those requiring face-to-face interaction. However, if most of these activities are already disrupted by voluntary behavior of consumers and workers that do not consume certain goods and services and perform certain tasks for the fear of contagion (as highlighted by Eichenbaum, Rebelo, and Trabandt 2020), then the additional damage of coercive policies may be negligible. Similarly, if these policies are established but compliance is low, their impact may be limited.

While it is clear that COVID-19 is causing economic disruption at unprecedented speed and scale (Baldwin and Weder di Mauro 2020; Gopinath 2020), the actual size of its economic impact and the relative importance of the underlying channels are still unknown. This poses an additional empirical challenge for the assessment of the economic impact of the NPIs. For instance, if most of the impact of the pandemic were due to the heightened uncertainty (Baker et al. 2020c) at the global level, then economic activity in a particular country or region may not respond to local health conditions or policies. This hypothesis is supported by earlier work by Carvalho et al. (2020) and Kahn et al. (2020) who find no evidence of a positive correlation between economic losses and the onset and severity of the pandemic, using, respectively, Spanish consumption data and U.S. labor market indicators.

In this paper, we use high-frequency indicators (HFIs) to provide a close-to-real-time assessment of the economic effects of the pandemic and NPIs. In the context of fast and massive economic disruptions due to the COVID-19 pandemic, the relatively slow frequency of most macroeconomic indicators represents a challenge for policymakers tasked with mitigating the economic impact of the crisis. In comparison, HFIs—such as electricity usage, unemployment insurance claims, measures of mobility based on location data, and other economic data collected by the private sector (Chetty et al. 2020)—are available with a short time lag and can be used to track economic activity as close as possible to “real time”.

Importantly, some of these indicators are available at daily frequency, which is useful for identifying abrupt changes in people’s behavior and economic activity. Exploiting variation in the timing of the NPIs across regions, we can show the extent to which NPIs affect mobility and economic activity by comparing the timing of their changes with the date when the policies are introduced.

We ask the following questions. First, is the COVID-19 pandemic a truly common shock, or do countries or regions that experience more extensive outbreaks also suffer more economically—in which case, what makes an economy more vulnerable to the COVID-19 shock? Second, how do people’s mobility respond to the outbreak? Third and most importantly, what is the role of mobility in transmitting the COVID-19 shock to the economy and how does it compare to the role of *de jure* NPIs?

Our main insight is that outbreaks and people’s mobility matter a great deal while *de jure* NPIs seem to matter less. We find that the economic impact of COVID-19 is mostly captured by changes in people’s mobility, while, so far, there is no robust evidence supporting additional impact from NPIs, during both the lockdown and reopening periods, especially in the United States.

More specifically, we find that European countries and U.S. states that have experienced larger outbreaks have experienced larger economic losses. Energy usage in Europe suggests that weekly output has declined by between 20 to 29 percent in mid-April in the median country and about twice as much in the hardest hit countries, such as Italy and Spain. Focusing on the heterogeneous impact of the shock across U.S. states, we find that states that are poorer and have lower share of workers that can work from home are more vulnerable.

We also find that most of the variation between states or countries is captured by the observed changes in people’s mobility, while the timing of *de jure* NPIs have no discernable effect on economic outcomes between March and mid-April. In fact, the decline in economic activity or mobility precedes rather than follows the introduction of such mitigation policies. This evidence is a warning against optimistic projections that the economic recovery will start once NPIs are lifted. The economy may not rebound unless workers and consumers feel safe about resuming their normal behavior. Consistent with this, we show that mobility and economic activity recovery started happening before the easing of NPIs. Moreover, there is no sharp acceleration in mobility and economic activity after the reopening.

The rest of the paper is structured as follows: we start by presenting the HFIs used in the analysis (Section II). We then discuss the effect of COVID-19 on economic activity in Europe (Section III) and the United States (Section IV). In Sections V and VI, we zoom in on the role of mitigation policies during the lockdown and the early phase of the reopening. We then discuss a few caveats to our analysis and conclude.

II. HIGH-FREQUENCY INDICATORS AND OTHER DATA

To monitor economic activity across European countries and U.S. states, we collect a variety of indicators, depending on data availability, from January 2020 to early May 2020.

First, we use data on electricity usage. This is a very useful high-frequency indicator of economic fluctuations (Chen et al. 2019; Cicala 2020) because electricity is an input in most economic activities and it is difficult to substitute in the short run. Data on electricity usage are available within the same day from the European Network of Transmission System Operators for Electricity (ENTSO-E) for 32 European countries. They are available from the U.S. Energy Information Administration for 64 Balancing Authorities (BAs) in the United States, who are responsible for monitoring and balancing the generation, load, and transmission of electric power within their region. We use GIS data to map BA regions to U.S. states. Since energy consumption exhibits substantial day-of-the-week fluctuations, we measure electricity usage with respect to the same day of the same week in 2019.²

Second, for the United States, we collect data on unemployment insurance (UI) claims, which are available at weekly frequency for all the states from the U.S. Department of Labor with only a one-week lag. These administrative data closely track labor market developments, so that an increase in UI claims is one of the earliest signs of rising unemployment and a weakening economy. We complement our analysis with data on hours worked, number of employees, and number of businesses from more than 100,000 local businesses (and their hourly employees) from the time-tracking tool Homebase (Bartik et al. 2020).³ This company covers primarily individual-owned restaurants and small- and medium-sized businesses in food service, retail, and other sectors that employ many hourly workers. Daily changes in hours worked, number of employees, and number of open businesses are computed by comparing a given day with the median of the same day of the week for the period January 4–31, 2020.

We focus on these indicators rather than other HFIs, such as hotel reservations or flight cancellations, as we aim to capture the overall pace of economic activity rather than focus on the hardest-hit sectors.⁴ We also abstract from long-term and persistent macroeconomic effects (Jorda, Singh, and Taylor 2020).

To track the severity of the pandemic in each country or region, we use the number of COVID-19 cases or deaths as a proxy for the severity of the outbreaks. We gather daily data on confirmed cases and deaths from the European Centre for Disease Prevention and Control (ECDC) for the European countries and from the COVID Tracking Project for U.S. states.

² For example, we compare the electricity usage on Tuesday March 31, 2020 with that on Tuesday April 2, 2019.

³ Homebase data should be interpreted with caution as the coverage is predominantly in small businesses and services.

⁴ Proprietary consumer data or asset prices can also provide useful information (Baker et al. 2020a, 2020b; Alfaro et al. 2020).

We use the Google Community Mobility Index to measure people’s mobility. This index is available on a daily basis both for European countries and U.S. states. Based on the number of times individuals visit certain places, daily change in mobility are computed with respect to the median value in the corresponding day of the week during the period of January 3 to February 6, 2020. The index is available for six categories (transit stations, workplaces, retail stores and recreation places, groceries and pharmacies, residential, and parks). To capture *de facto* social distancing, we focus on places which are the usual focus of social and economic life (transit stations, workplaces, retail stores and recreation places, groceries and pharmacies), excluding residential and parks.

Finally, we use data on the timing of adoption for several NPIs, including social distancing, closure of nonessential services, closure of public venues, school closures, and shelter-in-place orders, obtained from Hale et al. (2020) for Europe and from Keystone Strategy for the United States. Several other variables (e.g., population, employment) are drawn from standard sources (U.S. Census Bureau, Bureau of Economic Analysis, World Economic Outlook).

III. COVID-19 AND ECONOMIC ACTIVITY IN EUROPE

We compare current weekly electricity usage to the same week in 2019 for 32 European countries (counting only workdays and excluding weekends). Since early March, electricity usage has been declining in most countries, despite lower energy prices: in the median country in our sample, energy consumption was about 5 percent lower than in 2019 during weekdays. The decline has accelerated in April, as the health crisis and mitigation measures have become more widespread, with energy consumption about 15 percent lower than in 2019 during the weeks in the middle of April.⁵ The decline is largest in Italy—the first European country to experience an extensive outbreak and one of the hardest-hit so far: electricity usage has plummeted by almost 30 percent compared to 2019.

Cross-country analysis confirms the relationship between the extent of the health crisis and energy decline. Countries that have been experiencing a more severe outbreak, as measured by deaths per capita, and a sharper decline in people’s mobility have also reduced their energy consumption more (Figure 1).⁶ The estimated coefficient in Panel A suggests that during the acute stage of the pandemic, a doubling of the COVID-19 outbreak leads to a decrease in

⁵ A back-of-envelope calculation suggests that this decline in electricity usage corresponds to a weekly output loss of approximately 20 to 29 percent (in annualized terms). Approximately 30 percent of electricity is used by households in Europe. Therefore, assuming that neither the mix of input used in productive processes, nor the amount of electricity consumed domestically have changed during the pandemic, a 1 percent drop in electricity usage would correspond to a 1.43 ($=1/0.70$) percent drop in production. Alternatively, we estimate the elasticity of electricity with respect to GDP using annual data and exploiting banking crises as shocks to economic activity (see Table A1). We obtain coefficient values ranging from 0.53 to 0.78, implying that, historically, a 1 percent drop in electricity usage is associated with 1.3 to 1.9 percent drop in output.

⁶ The figure plots data for the week of April 11 when electricity usage reached its bottom. Results for other weeks between mid-March and late April are similar, also see Table A4.

energy consumption of approximately 2.3 percent. This is a non-trivial amount, given that the number of cases doubled every 2 to 3 days during the early phase of the epidemic. Mobility has, in general, stronger explanatory power than deaths per capita (Panel B; also see Table A2). These figures come with all the well-known caveats of extrapolation from cross-sectional results to the aggregate (Nakamura and Steinsson 2018), together with the additional issue of potentially severe non-linearities (the small sample size thus far limit a thorough assessment of these non-linearities).

These results are robust to controlling for weather conditions or differences in sectoral composition of output—other important factors for electricity usage. We proxy for weather conditions with the average temperature difference between 2020 and the same week of 2019. To capture the heterogenous sectoral composition of output, we use either the share of manufacturing in national production or the expected GDP loss for a six-week lockdown as calculated by Barrot, Basile, and Sauvagnat (2020) using differences in sectoral composition and propensity to telework across countries (see Table A2).⁷

IV. COVID-19 AND ECONOMIC ACTIVITY IN THE UNITED STATES

Electricity usage has also decreased sharply in the United States: average daily usage in early April was 5 percent lower than it was during the same period in 2019. More strikingly, 30 million new unemployment insurance claims have been filed in the first six weeks since the pandemic, implying a dramatic reduction in employment and labor force participation (see Bick and Blandin 2020; Cajner et al. 2020; Coibion, Gorodnichenko, and Weber 2020, among others). It took almost one year to reach that number in the wake of the Lehman Brothers' bankruptcy.

Cross-sectional analysis shows that the decline in electricity usage and job losses, as measured by the weekly filings for unemployment insurance between March 8 and April 25, are concentrated in states that have been hit harder by COVID-19, as measured by the number of COVID-19 deaths per capita over the same period (Figure 2).⁸ This evidence is corroborated when looking at the change in the number of hours worked (Figure A1, panel A) and it is in line with recent evidence shown for U.S. cities during the 1918 flu pandemic (Correia, Luck, and Verner 2020).⁹

⁷ The sectoral composition of output controls for sectoral heterogeneity in electricity usage (e.g. manufacturing is more energy intense than other sectors) and exposure to the COVID-19 shock (e.g. some industries are hit harder by mitigation policies due to the lack of teleworking arrangements).

⁸ In our analysis for Europe, we are not able to look at the labor market given that high-frequency data like weekly UI claim filings are not available.

⁹ Related evidence on labor market outcomes is also discussed by Doerr and Gambacorta (2020) and Béland et al. (2020), among others. Note that, the results on the UI claims differ from those shown by Kahn et al. (2020), who look at the UI claims only until April 11 and, more importantly, measure the extent of the pandemic by the number of cases per capita in the week of March 14, when the outbreak had not yet reached all U.S. states.

We then exploit both the time and cross-sectional dimensions of the data and estimate a model with time and state fixed effects. In this case, we observe that—*within state*—as the number of COVID-19 cases increases, electricity usage decreases while filings for UI claims increases. The results are economically significant and summarized in Figure A2. For electricity usage, the average elasticity is 0.8 for continental U.S. states, indicating that a doubling of the number of cases leads to a decrease in energy consumption of 0.8 percent. For UI claims, the average elasticity is 0.11, indicating that a doubling of the COVID-19 positive cases is associated with 11 percent more claims. However, this elasticity weakens over time—in the first week during which the number of claims spiked, the elasticity was close to 0.3. The same pattern is present if we look at the decline in the number of hours worked (Figure A3), suggesting that the labor market has reacted very fast to the outbreak and the related social distancing measures put in place to contain the pandemic.¹⁰

Finally, the labor market reaction to the pandemic is heterogenous across U.S. states, not only in relation to the intensity of the COVID-19 shock, but also depending on institutional and economic characteristics. In particular, for a given severity of the outbreak, job losses have increased more in poorer states, in states with a lower employment share in hotels and leisure, as well as a lower share of jobs that can be done from home (as measured by Dingel and Neiman 2020), and in states that do not have in place laws for paid sick leave (Figure A2, panel A).¹¹ The impact on electricity usage is also stronger among states with a lower share of jobs that can be done at home (Figure A2, panel B).

V. COVID-19, ECONOMIC CONTRACTION, AND MITIGATION EFFORTS

We now turn to the channel through which the COVID-19 shock transmits to the economy, with a focus on the role of people’s mobility and NPIs—two related but distinct issues. People’s mobility is a *de facto* measure of mitigation efforts and captures *de jure* NPIs, such as school closures and shelter-in-place orders, but also compliance and voluntary social distancing by individuals.

We find that mobility is positively associated with electricity usage (Figure 3, panel A) and negatively associates with UI claims (Figure 3, panel B). In contrast, the relationship between *de jure* NPIs and economic contraction is weaker. Figure 2 shows that in the United States early NPIs adopters do not perform, on average, worse than late adopters neither in terms of electricity usage nor the number of UI claims. The cross-sectional correlation between electricity usage across European countries and the stringency of mitigation policies (Hale et al. 2020) is statistically significant only in the early weeks of the pandemic but not in April

¹⁰ Similar findings are also valid if we use the change in the number of employees working or open local businesses. Results available upon request.

¹¹ All these results are reported in Table A3. Findings are similar if we look at the change in (i) hours worked, (ii) the number of employees, and (iii) open businesses in the Homebase sample of local businesses. Results are available upon request.

(continued...)

(Table A4). In the United States, the timing of *de jure* NPIs is not significantly associated with the number of UI claims per capita, whether we control for the size of the local outbreak and other state-level characteristics or not (Table A5).¹²

In other words, *de jure* NPIs are only part of the story. Compliance and voluntary social distancing matter. This is also in line with the Swedish experience, albeit the situation is still unfolding: the observed decline in electricity usage in Sweden—which has adopted relatively less strict mitigation policies but where many have been practicing social distancing by choice—is fairly similar to that in neighboring countries although the decline in mobility is smaller (Figure 1, panel B). Data from Denmark and Sweden also show that consumer spending dropped by 25 percent in Sweden compared to a slightly higher drop of 29 percent in Denmark, which was similarly exposed to the pandemic but adopted much stricter containment measures (Andersen et al. 2020). Furthermore, the similar economic outcomes seem to be accompanied by higher death rates than other Nordic countries (Bricco et al. 2020).

Furthermore, using daily data on a large sample of local businesses,¹³ we find that the sharp decline in hours worked—relative to January—begins well before the introduction of *de jure* NPIs at the state level (Figure 5, panel A), and it is quite common across states, as shown also by Bartik et al. (2020). Similarly, by the time stay-at-home orders were adopted in Europe, the decrease in mobility and electricity usage was already sizeable (Figure 5, panel B). Interestingly, relative to local COVID-19 caseloads, mobility dropped earlier in the United States than in Europe although NPIs were adopted around the same phase of the epidemic. The United States reached 1,000 COVID-19 cases 11 days after Europe. The first stay-at-home order in the United States (in California) was issued 10 days after the first stay-at-home order in Europe (in Italy). But mobility in the United States fell by 20 percent compared to January 2020 just 4 days after Europe (Figure 4). Moreover, the early NPIs—school closures in many cases—triggered the decline in mobility and economic activity in Europe (Figure 5, panel D) but even they seem to have been anticipated in the United States (Figure 5, panel C).

A likely explanation of this difference is that Americans “learnt” from the European experience and practiced voluntary distancing and closures before *de jure* NPIs were adopted. Increased news coverage on COVID-19 during the second week of March is also consistent with this increased “awareness” explanation: on March 11, for instance, the WHO declared COVID-19 a pandemic, the NBA suspended its games, and Hollywood star Tom Hanks revealed that he had tested positive.

¹² As before, findings are similar if we look at the change in (i) hours worked, (ii) the number of employees, and (iii) open businesses in the Homebase sample of local businesses. Results are available upon request. In a similar vein, personal vehicle travel declined both in states that imposed stay-at-home orders early in March and in those that imposed such orders later, although the decline in the former was slightly more (Cicala et al. 2020).

¹³ The data come from Homebase. Sectors that are hit harder and earlier by the pandemic, such as restaurants, may be overrepresented in this data source.

(continued...)

These findings suggest that avoiding or delaying NPIs may not fully shield an economy from the COVID-19 shock,¹⁴ and that the depression of economic activity may persist even after mandatory lockdown measures are lifted if people continue to voluntarily limit their mobility.

VI. COVID-19, LIFTING OF MITIGATION MEASURES, AND ECONOMIC RECOVERY

The lifting of mitigation policies in many countries and states provides additional evidence on the role of *de jure* NPIs and voluntary social distancing. In the 45 US states that have allowed nonessential businesses to reopen since late April, mobility and hours worked show a gradual recovery starting about two weeks before the reopening (Figure 6, panel A).¹⁵ The gradual increase in mobility before official reopening may be due to lockdown fatigue and lower perceived risk from infection (for instance, because daily case numbers start coming down, or the outbreak is no longer the top story in the news headlines, or people update their beliefs about the virus every day they or someone they know do *not* get infected). The dynamics of hours worked can be partially explained by the fact that some services started operating even before the reopening (e.g., food deliveries and curbside pick-up). In addition, small businesses may have to start re-hiring to get ready for the reopening.

A similar picture emerges from analyzing the easing of NPIs in European countries (Figure 6, panel B). In this exercise, we date the reopening as the day of the first reduction in the stringency index of mitigation policies (Hale et al. 2020) by at least 5 points. We again observe that mobility starts improving about two weeks before reopening. The trend in electricity usage is less clear. There is a first pick-up about 20 days before the easing of the stringency index in tandem with mobility, followed by a modest decrease and a second pick-up three days before the reopening. This second pick-up continues for about a week after the reopening and then appears to flatten.

Two main findings stand out. First, there are strong anticipation effects in both mobility and economic activity. Second, there is no clear evidence of any acceleration soon after the easing of restrictions. These findings suggest that, in the reopening phase, people’s behavior matters more for the resumption of activities than the timing of the reopening. In addition, the evidence of anticipation effects in mobility and economic activity—seen also in the lockdown phase (Figure 5)—suggests caution in interpreting changes in economic activity around changes in *de jure* NPIs.

¹⁴ This could be because people’s behavior changes even in the absence of mandatory restrictions and/or due to spillovers from other regions (for instance, through supply chain disruptions or reduced demand for travel).

¹⁵ While data on hours worked from Homebase has to be interpreted with caution as they refer to hourly workers predominantly in small businesses and services, consumer spending shows a similar pattern (see <https://tracktherecovery.org/>).

(continued...)

VII. DISCUSSION AND CONCLUSION

The use of cases or death counts as a measure of the COVID-19 shock at the local level must be accompanied by three caveats. First, the reported numbers depend on testing policies and capabilities, which might be different across countries and states and evolve over time.¹⁶ Second, there is an interaction between mitigation policies and new case and death counts, as well as economic activities. As a result, national and local authorities may face a trade-off between slowing the pandemic and preserving economic activity, at least in the short run. Third, the exact reasons why some areas have been experiencing earlier or more intense outbreaks are still largely unknown. Therefore, hardest-hit areas might be different from other areas and, importantly for any empirical analysis, what makes an area susceptible to large outbreaks could be correlated with what also makes the economic impact sizeable (e.g., the prevalence of nonessential service jobs, industry composition, etc.).

Our analysis relies on the heterogeneous timing and intensity of the COVID-19 outbreak across different European countries and U.S. states to provide useful evidence to guide policymaking to “flatten the recession curve” (Gourinchas 2020).

First, the sharp decline in electricity usage and the unprecedented spike in UI claims highlight that this crisis is novel not only for its magnitude, but also for the speed at which the economy and specifically the labor market are affected. With entire sectors of the economy on a lockdown and the need to “flatten the curve,” millions of workers have immediately lost their jobs. These numbers are a call for an unprecedented policy response, which should be more similar in spirit to the reaction to wars and natural disasters, rather than a standard macroeconomic stimulus to support demand. A mix of monetary, fiscal, and financial measures should be aimed at minimizing disruptions and scarring from the lockdown, by providing sizeable, targeted support to households and businesses to cope with the “hibernation” of the economy and to be able to jump-start soon after the health crisis will be over.

Second, our evidence suggesting that the heterogeneous impact of COVID-19 is mostly due to observed mobility instead of the adoption of *de jure* NPIs is a warning against optimistic projections that the economic recovery will start once NPIs are officially lifted. The economy may not rebound unless workers and consumers feel safe about resuming their normal activities. Early evidence on reopening of non-essential business activities and the easing of NPIs indicates that this is in fact the case. As countries move forward with loosening of mitigation policies, analyses such as ours could guide decisions not only on the pace and breadth of lifting mitigation policies but also on other measures that may be needed to restore confidence and trust for people to get back to pre-COVID-19 behaviors.

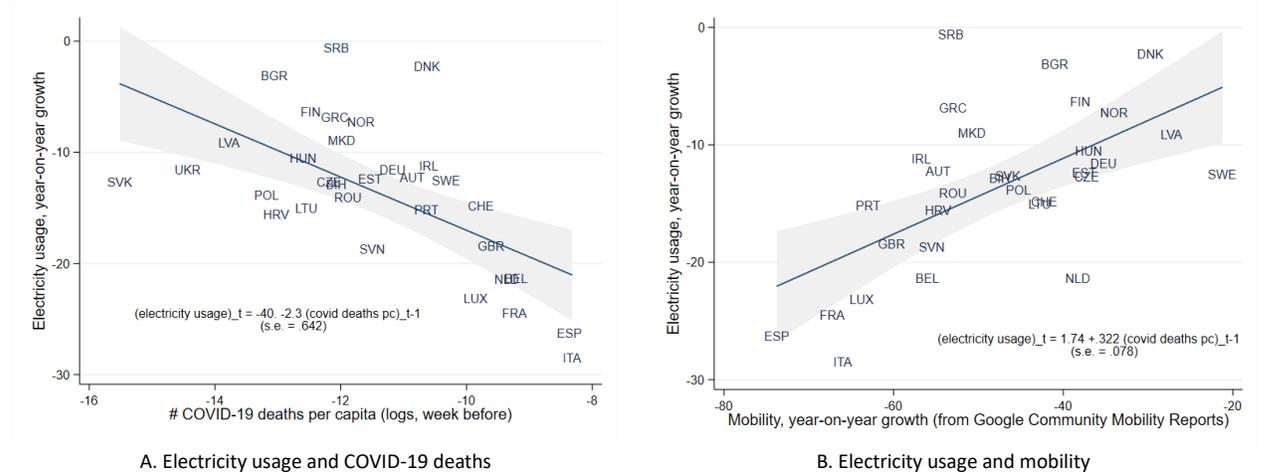
¹⁶ Our results are robust to controlling for the total number of tests, which partially mitigates this concern.

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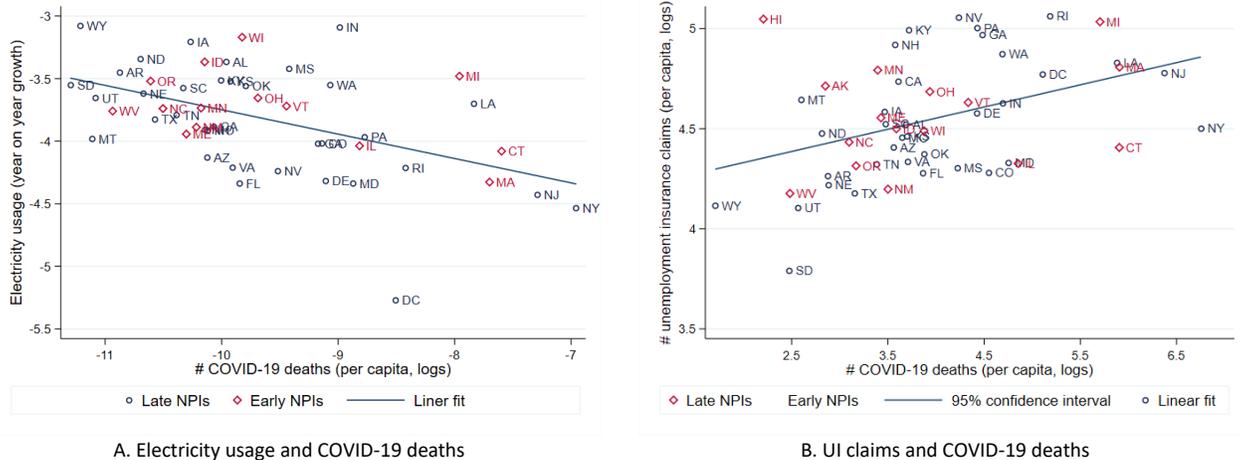
FIGURE 1. COVID-19, Electricity Usage, and Mobility in Europe



Source: [ENTSO-E](#), [ECDC](#), [Google Community Mobility Reports](#).

Notes: Panel A plots the percent change in weekly electricity usage relative to the same week in 2019 and the number of COVID-19 deaths per capita in 32 European countries. Panel B plots the percent change in weekly electricity usage relative to the same day of the same week in 2019 and the percent change in visits public places (retail and recreation, grocery and pharmacy, transit stations, and workplaces) within a geographic area relative to the pre-COVID-19 period. In both charts, the solid line plots a linear fit and the gray area shows the 95 percent confidence interval bands. The sample is the week ending on April 11, 2020.

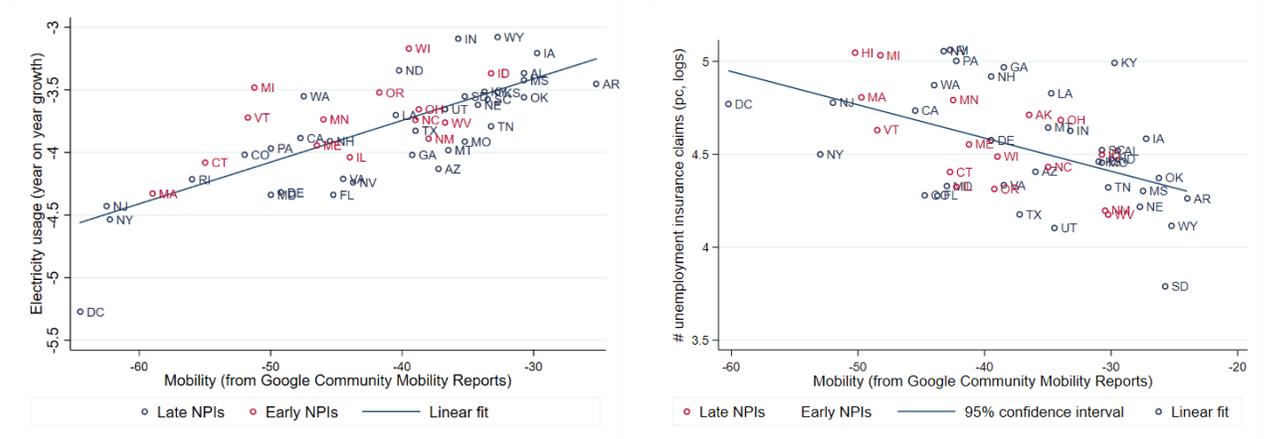
FIGURE 2. COVID-19, Electricity Usage, and UI Claims in the United States



Source: U.S. Energy Information Administration, U.S. Department of Labor, U.S. Census Bureau, <https://covidtracking.com>, [Google Community Mobility Reports](#).

Notes: This figure plots electricity usage (in logs of megawatt hours, compared to the same day of the same week in 2019, Panel A) and the total number of unemployment insurance claims per capita (in logs, Panel B) against the number of COVID-19 deaths per capita (in logs). The sample period is March 1-April 5 (Panel A) and March 8-April 25 (Panel B). The solid line plots a linear fit. Panel A controls for the share of service industry. The slope is -0.19 (s.e.=0.05) in Panel A and 0.11 (s.e.=0.04) in Panel B. States are divided between early (red labels) and late (blue labels) NPI adopters. The NPIs considered are social distancing, closure of nonessential services, closure of public venues, school closures, and shelter-in-place orders. A state is considered an early NPIs adopter if all these five policies have been implemented within a week from the day in which the first death in the state has been recorded.

FIGURE 3. Mobility, Electricity Usage, and UI Claims in the United States



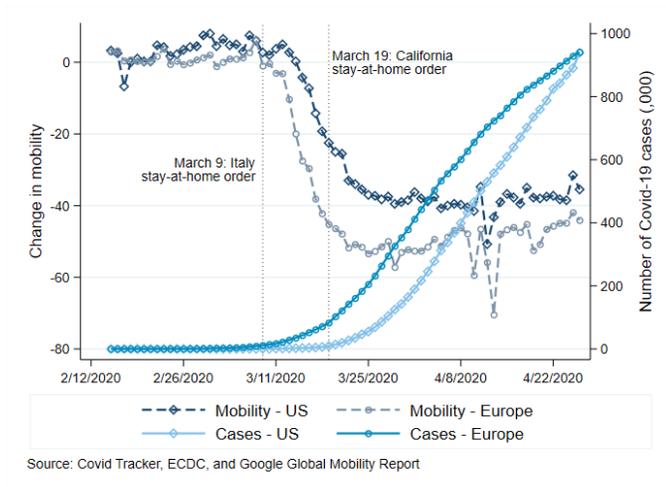
A. Electricity usage and mobility

B. UI claims and mobility

Source: U.S. Energy Information Administration, U.S. Department of Labor, U.S. Census Bureau, <https://covidtracking.com>, <https://github.com/Keystone-Strategy/covid19-intervention-data>, [Google Community Mobility Reports](https://www.google.com/covid19/mobility/).

Notes: This figure plots electricity usage (in logs of megawatt hours, compared to the same day of the same week in 2019, Panel A) and the total number of unemployment insurance claims per capita (in logs, Panel B) against the percent change in visits to various places (grouped under four categories: retail & recreation, grocery & pharmacy, transit stations, and workplaces) within a geographic area relative to the pre-COVID-19 period, at the state level. The sample period is March 1-April 4 (Panel A) and March 8-April 25 (Panel B). The solid line plots a linear fit. Panel A controls for the share of service industry. The slope is 0.033 (s.e.=0.004) in Panel A and -0.017 (s.e.=0.004) in Panel B. States are divided between early (red labels) and late (blue labels) NPI adopters. The NPIs considered are social distancing, closure of nonessential services, closure of public venues, school closures, and shelter-in-place orders. A state is considered an early NPIs adopter if all these five policies have been implemented within a week from the day in which the first death in the state has been recorded.

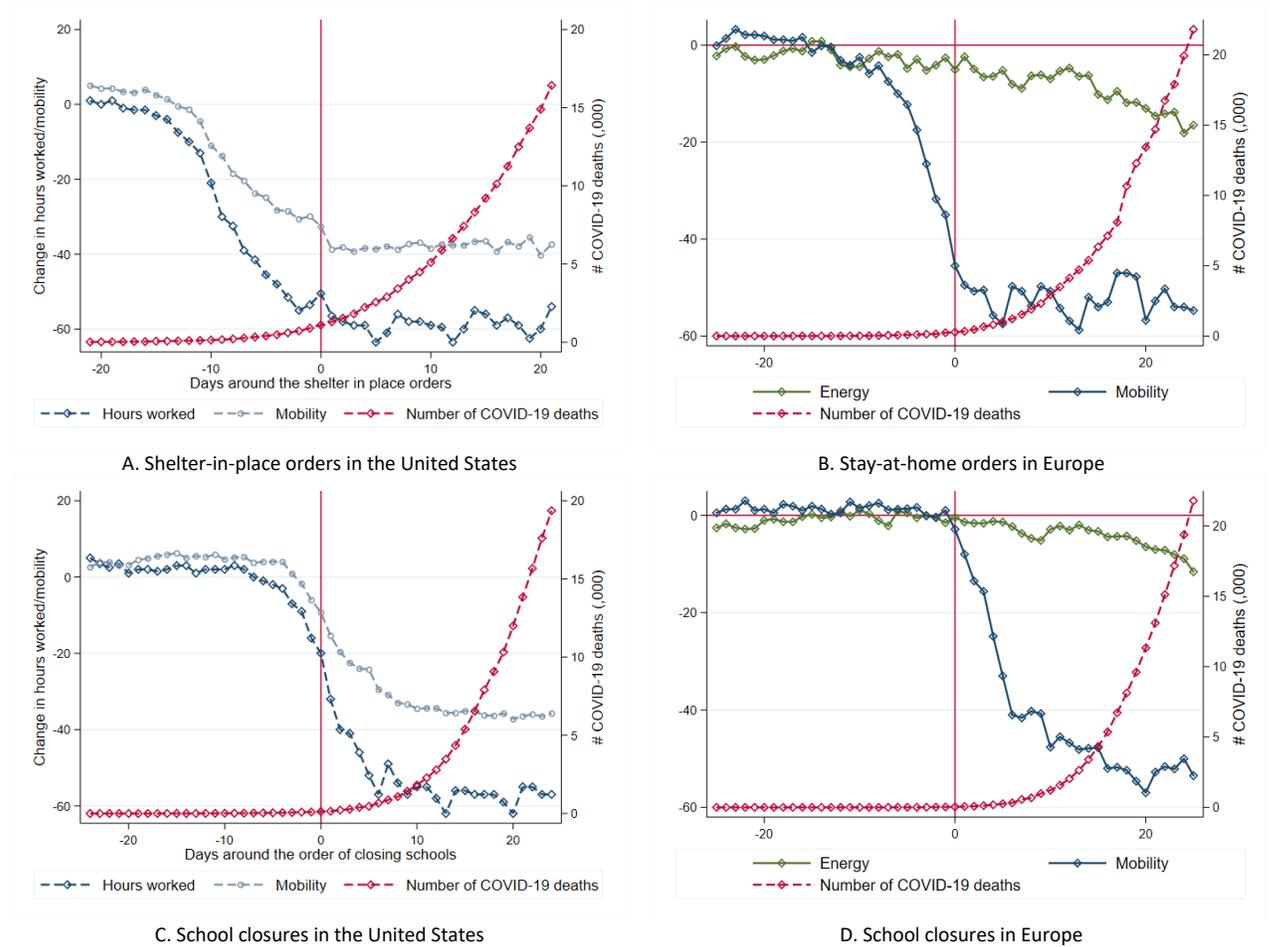
FIGURE 4. COVID-19, NPI Timing, and Mobility in Europe versus the United States



Source: <https://covidtracking.com>, [Google Community Mobility Reports](https://www.google.com/covid19/mobility/), [Homebase](https://homebase.ecdc.europa.eu/en), [ECDC](https://ecdc.europa.eu/en), [ENTSO-E](https://ec.europa.eu/entso-e/).

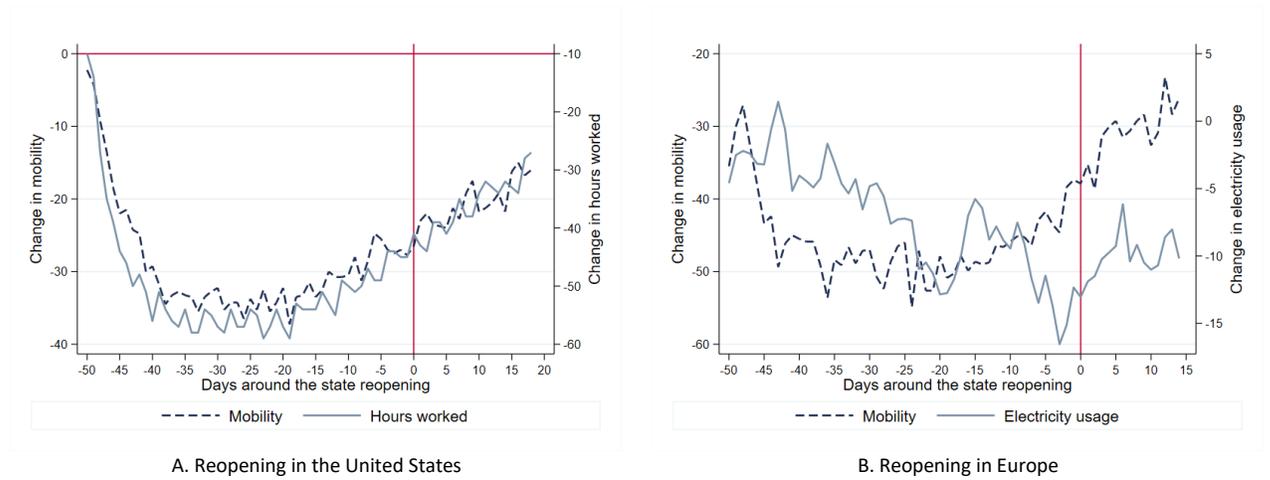
Notes: The chart plots the cumulative number of COVID-19 cases and changes in mobility relative to the pre-COVID-19 period in the United States and Europe. The vertical lines are March 9 and March 19, 2020—the dates when state-at-home orders were issued in Italy and California, respectively.

FIGURE 5. COVID-19, NPI Timing, Mobility, and Economic Activity



Source: <https://covidtracking.com>, <https://github.com/Keystone-Strategy/covid19-intervention-data>, [Google Community Mobility Reports](#), [Homebase](#), [ECDC](#), [ENTSO-E](#), [Hale et al. \(2020\)](#).

Notes: Panels A and C plot the changes in hours worked for a large sample of small businesses and in mobility (both relative to the pre-COVID-19 period) for the median U.S. state, and the cumulative number of COVID-19 deaths for all U.S. states in the sample. The x-axis is the number of days before/after the introduction of NPIs (shelter-in-place in Panel A and school closures in Panel C). The sample only includes states that have adopted the policy by April 30. Figures based on other NPIs, such as closure of non-essential business or public venues, are qualitatively and quantitatively similar. Panels B and D plot the median change in electricity usage—with respect to the previous year—the median change in mobility relative to the pre-COVID-19 period, across European countries, and the cumulative number of COVID-19 deaths for all European countries. The x-axis reports the number of days before/after the introduction of NPIs (stay-at-home orders in Panel B and school closures in Panel D). The sample only includes European countries that have adopted the policy by April 10. NPIs introduction and classification is based on Hale et al. (2020).

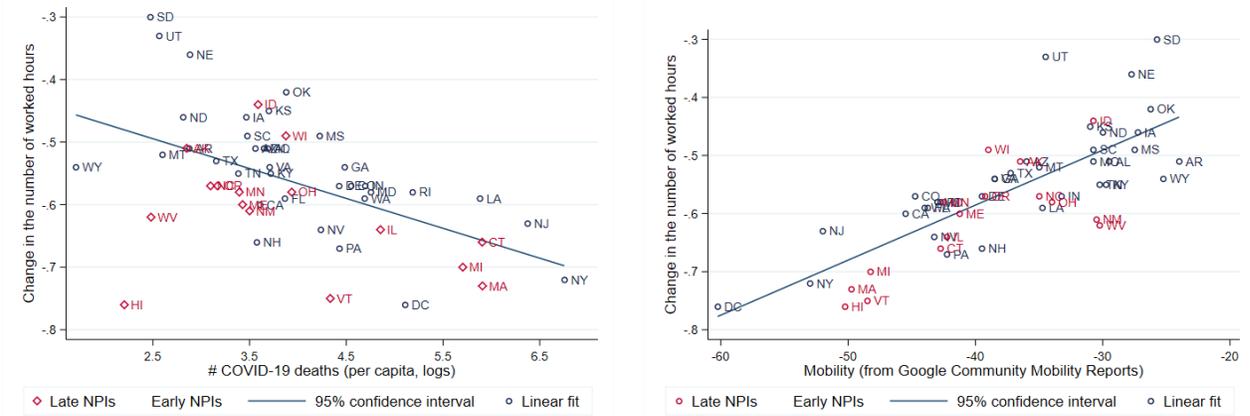
FIGURE 6. Reopening, Mobility, and Economic Activity

Source: <https://tracktherecovery.org/>, [Google Community Mobility Reports](#), [Homebase](#), [ENTSO-E](#), [Hale et al. \(2020\)](#).

Notes: Panel A plots the changes in hours worked for a large sample of small businesses and in mobility (both relative to the pre-COVID-19 period) for the median U.S. state. The x-axis is the number of days before/after the reopening of nonessential businesses. The sample only includes 45 states that have reopened by May 30. A figure based on the lift of the state-at-home orders is qualitatively and quantitatively similar. Panel B plots the median change in electricity usage—with respect to the previous year—the median change in mobility relative to the pre-COVID-19 period, across 21 European countries. The x-axis reports the number of days before/after the relaxation of NPIs (the day 0 is the first time that the Oxford stringency index (Hale et al. 2020) declines by at least 5 points).

APPENDIX FIGURES AND TABLES

FIGURE A1. COVID-19, Mobility, and Hours Worked in the United States



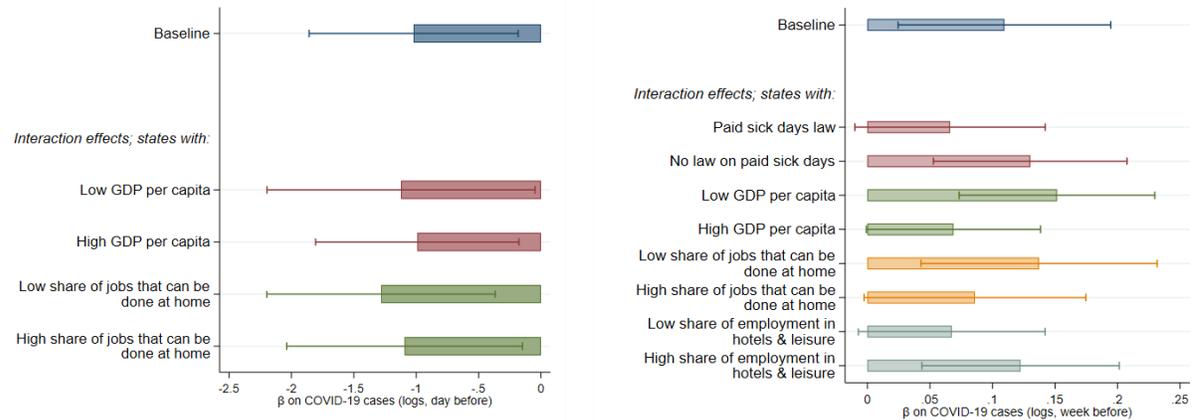
A. COVID-19 and hours worked

B. Mobility and hours worked

Source: U.S. Department of Labor, Homebase, <https://covidtracking.com>, <https://www.kff.org/other/state-indicator/paid-family-and-sick-leave/>.

Notes: This figure plots the change in the number of worked hours in local businesses (measured with respect to the period Jan 4-31, 2020) against the number of COVID-19 deaths per capita (in logs, Panel A) and the percent change in visits to various places (grouped under four categories: retail & recreation, grocery & pharmacy, transit stations, and workplaces) within a geographic area relative to the pre-COVID-19 period, at the state level. The sample period is March 8-April 25. The solid line plots a linear fit. The slope is -0.048 (s.e.=0.011) in Panel A and 0.010 (s.e.=0.001) in Panel B. States are divided between early (red labels) and late (blue labels) NPI adopters. The NPIs considered are social distancing, closure of nonessential services, closure of public venues, school closures, and shelter-in-place orders. A state is considered an early NPIs adopter if all these five policies have been implemented within a week from the first death in the state has been recorded.

FIGURE A2. COVID-19, Electricity Usage, and UI Claims: State Heterogeneity



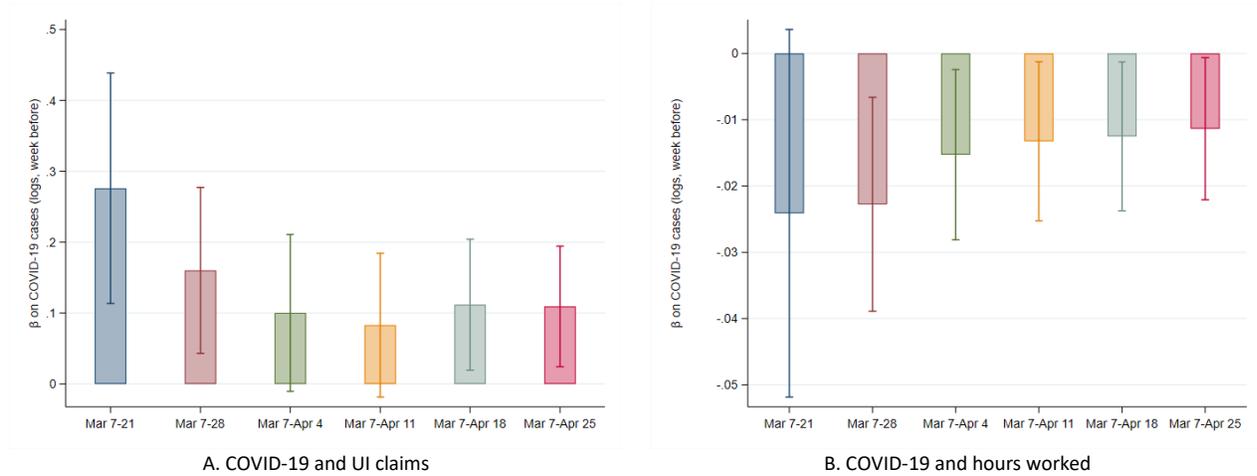
A. COVID-19 and electricity usage

B. COVID-19 and UI claims

Source: U.S. Department of Labor, U.S. Energy Information Administration, Bureau of Economic Analysis, <https://covidtracking.com>, <https://www.kff.org/other/state-indicator/paid-family-and-sick-leave/>, [Dingel and Neiman \(2020\)](https://www.kff.org/other/state-indicator/paid-family-and-sick-leave/).

Notes: Results of estimating the equation: $y_{s,t} = \alpha_s + \gamma_t + \beta * COVID_{s,t-1} + \delta * X_s * COVID_{s,t} + \varepsilon_{s,t}$, where s is a U.S. state, t is a day between March 1 and April 4, 2020 (Panel A) or a week between March 7 and April 25, 2020 (Panel B). $y_{s,t}$ is electricity usage (Panel A), in logs of MWh, relative to the same day of the week of the same week in 2019) or the number of unemployment insurance claims in that week (in logs) (Panel B). $COVID_{s,t-1}$ is the number of COVID-19 cases in the previous day (Panel A) or week (Panel B) (in logs), X_s is a vector of state-level characteristics, α_s and γ_t are, respectively, state and week fixed effects. The sample is a balanced panel with $t=49, n=50$ (Panel A) or $t=7, n=51$ (Panel B). The top bar plots the coefficient of the baseline regression (β), while the other bars plot the coefficients ($\beta + \delta$) separately for states with and without paid sick days laws; low and high GDP per capita; low and high share of jobs that can be done from home; and low and high share of employment in hotels and leisure. Low is defined by the first quartile of the state distribution. The bars show the associated 90 percent confidence intervals. Standard errors are clustered by state.

FIGURE A3. COVID-19, UI Claims, and Hours Worked: Changes over Time



Source: U.S. Department of Labor, Bureau of Economic Analysis, Homebase, <https://covidtracking.com>, <https://www.kff.org/other/state-indicator/paid-family-and-sick-leave/>, [Dingel and Neiman \(2020\)](#).

Notes: Results of estimating the equation: $y_{s,t} = \alpha_s + \gamma_t + \beta_t * Covid_{s,t-1} + \varepsilon_{s,t}$, where s is a U.S. state, t is a week between March 7 and April 25, 2020. $y_{s,t}$ is the number of unemployment insurance claims in a that week (in logs) (Panel A) or the change in the number of worked hours in local businesses (measured with respect to the period Jan 4-31, 2020, Panel B). $Covid_{s,t-1}$ is the number of COVID-19 cases in the previous week (in logs), and α_s and γ_t are, respectively, state and week fixed effects. The sample is a balanced panel with $t=7$, $n=51$ (Panel B). Each bar plots the β coefficients estimating the equation above separately over different time periods, as indicated on the x-axis. The bars show the associated 90 percent confidence intervals. Standard errors are clustered by state.

TABLE A1. Electricity and Output

Dep. Vars.: (in delta log per capita)	Electricity			GDP			Electricity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP	0.0801 (0.101)	0.2703*** (0.068)	0.2861*** (0.063)				0.7756** (0.333)	0.5287* (0.279)	0.5602** (0.271)
Banking crisis (t to t-2)				-0.0322*** (0.006)	-0.0374*** (0.011)	-0.0368*** (0.010)			
Time Frame	2001 to 2019	1981 to 2019	1961 to 2019	2001 to 2019	1981 to 2019	1961 to 2019	2001 to 2019	1981 to 2019	1961 to 2019
Estimator	OLS			OLS (First Stage)			IV		
Observations	694	1,329	1,554	700	1,475	2,065	694	1,329	1,554
F-stat				28	12	12			
R2	0.131	0.084	0.102	0.322	0.086	0.073			
R2-within	0.0008	0.0322	0.0374	0.0473	0.0189	0.0166			

Source: EAI, ENTSO-E, WEO, Laeven and Valencia (2020).

Notes: The table presents the results of estimating the linear regression:

$\Delta Electricity_{c,t} = \beta * \Delta GDP_{c,t} + \gamma_c + \alpha_c * t + \varepsilon_{c,t}$. where c and t indicate a country and a year in our sample, γ_c are country fixed effects, and α_c capture country-specific time trends. Estimating the parameter β allows us to infer the unobserved drop in GDP caused by the COVID-19 shock as:

$\Delta GDP_{c,COVID} = \frac{\Delta Electricity_{c,COVID}}{\beta}$. Estimates of β with OLS are reported in columns (1), (2), and (3) which refer to three different sample periods, all ending in 2019 and starting, respectively, in 2001, 1981, and 1961. As an alternative empirical strategy, we instrument the changes in GDP with the banking crises reported by Laeven and Valencia (2020, Systemic Banking Crises Revisited). Banking crises are a useful instrument as they are unlikely to affect energy production directly but only through their effect on economic activity, as they are often followed by sharp recessions. We therefore estimate a two-stage least squares model where we instrument delta logs of GDP with a dummy equal to one if that country experienced a banking crisis in that year or in the previous two (different timing choices lead to less power in the first stage). The first stage of the model is presented in columns (4), (5), and (6) for the three different time periods. The second stage results are reported in columns (7), (8), and (9). All variables are in delta log per capita except for the banking crisis dummies. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent level, respectively.

TABLE A2. COVID-19 and Electricity Usage in Europe: Robustness

Dep. Var.:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Electricity consumption: week ending on Apr 11									
Log of deaths per capita (stock, previous week)	-2.3924*** (0.643)	-2.3349*** (0.822)	-4.6048*** (0.860)	-2.3924*** (0.643)	-1.5626** (0.748)					
Mobility						0.3225*** (0.079)	0.3250*** (0.072)	0.4717*** (0.085)	0.3225*** (0.079)	0.3320*** (0.097)
Share of Manufacturing in Production		6.5321 (14.724)					9.3654 (7.631)			
Expected lockdown impact, Barrot et al. 2020			1.8036 (1.073)					-1.6722* (0.872)		
Average Temperature					-0.6184*** (0.214)					-0.7498*** (0.197)
Average Temperature (same week 2019)					0.3576 (0.242)					0.8145*** (0.196)
Observations	32	25	15	32	30	31	25	15	31	29
R2	0.374	0.421	0.652	0.374	0.484	0.364	0.530	0.657	0.364	0.608

Source: [ENTSO-E](#), [ECDC](#), [Google Community Mobility Reports](#), OECD, Barrot, Basile, and Sauvagnat (2020), NOAA

Notes: Results of estimating the equations: $y_c = \alpha + \beta * COVID_c + \delta * X_c + \varepsilon_c$ and $y_c = \alpha + \beta * Mobility_c + \delta * X_c + \varepsilon_c$, where y_c is the year-on-year change in weekly (workday) electricity consumption in one of 32 European countries during the week ending on April 11, 2020; $COVID_c$ is the log of the total deaths due to COVID-19 per capita; $Mobility_c$ is the change in mobility from Google Community Report. X_c is a country-level control, which is either the share of manufacturing in national production in 2017 (OECD), or the expected impact of a six-week lockdown calculated by Barrot et al. (2020) using data on sectoral composition of output and propensity to work-from-home, or the average temperature in the country in that week and same week in 2019.

TABLE A3. COVID-19 and UI claims in the United States

Dep. Var.: Unemployment insurance claims (logs)	(1)	(2)	(3)	(4)	(5)
COVID-19 cases (logs, week earlier)	0.1094** (0.051)	0.1300*** (0.046)	0.0686 (0.042)	0.0858 (0.053)	0.1222** (0.047)
<i>Interaction with:</i>		-0.0641*** (0.023)			
Paid sick day laws in place			0.0829*** (0.024)		
Low per capita GDP				0.0513* (0.028)	
Low share of jobs that can be done at home					-0.0549*** (0.020)
Low employment share in hotels & leisure					
	356	356	356	314	356
Observations	0.952	0.954	0.955	0.955	0.953
R2-adjusted	0.0234	0.0646	0.0975	0.0615	0.0557
R2-within	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes

Source: U.S. Department of Labor, U.S. Energy Information Administration, Bureau of Economic Analysis, <https://covidtracking.com>, <https://www.kff.org/other/state-indicator/paid-family-and-sick-leave/>, [Dingel and Neiman \(2020\)](#).

Notes: Results of estimating the equation: $y_{s,t} = \alpha_s + \gamma_t + \beta * COVID_{s,t-1} + \delta * X_s * COVID_{s,t} + \varepsilon_{s,t}$, where s is a U.S. state, t is a week between March 7 and April 25, 2020. $y_{s,t}$ is the number of unemployment insurance claims in a that week (in logs). $COVID_{s,t-1}$ is the number of COVID-19 cases in the previous week (in logs), X_s is a vector of state-level characteristics, α_s and γ_t are, respectively, state and week fixed effects. The sample is a balanced panel with $t=7$, $n=51$. The "low" category (for: per capita GDP, share of jobs that can be done from home, and employment share in hotel and leisure) is defined by the first quartile of the state distribution. Standard errors are clustered by state.

TABLE A4. COVID-19 and Electricity Usage in Europe: Different Weeks

Dep. Var.: Electricity consumption	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	week ending on Mar 14				week ending on Mar 28				week ending on Apr 4				week ending on Apr 11				week ending on Apr 18			
Log of deaths per capita (stock, previous week)	-1.7416*		-1.2450		-2.4438**		-2.2885***		-2.5632**		-1.8815**		-2.3924***		-1.8467**		-1.1120		0.2260	
	(0.978)		(0.875)		(0.915)		(0.811)		(1.000)		(0.872)		(0.643)		(0.714)		(0.696)		(0.737)	
Mobility		0.2586***	0.1955***			0.3149***	0.2150**			0.5226***	0.4061***			0.3225***	0.2160**			0.4608***	0.4750***	
		(0.066)	(0.065)			(0.110)	(0.090)			(0.103)	(0.092)			(0.079)	(0.080)			(0.102)	(0.122)	
Stringency Index				-0.1911**				-0.1121				-0.1523				-0.0832				-0.1945
				(0.077)				(0.132)				(0.170)				(0.139)				(0.123)
Observations	32	31	31	29	32	31	31	29	32	31	31	29	32	31	31	29	32	31	31	29
R2	0.132	0.291	0.334	0.249	0.226	0.207	0.375	0.033	0.250	0.454	0.551	0.039	0.374	0.364	0.524	0.018	0.056	0.460	0.462	0.081

Source: [ENTSO-E](#), [ECDC](#), [Google Community Mobility Reports](#), Hale et al. (2020)

Notes: Results of estimating equations: $y_c = \alpha + \beta * X_c + \varepsilon_c$ where y_c is the year-on-year change in weekly (workday) electricity consumption in one of 32 European countries during a week between March 8 and April 18. X_c is either the log of the total deaths due to COVID-19 per capita, or the change in mobility from Google Community Report, or the Index of Stringency of COVID-19 Government Intervention from Hale et al (2020).

Table A5. Unemployment Insurance Claims, NPIs, and COVID-19 in the United States

Dep. Var.: Unemployment insurance claims per capita (logs)	(1)	(2)	(3)	(4)	(5)	(6)
Early NPIs	0.0406 (0.075)					
Early nonessential service closure		0.0205 (0.071)				
Early public venue closure			0.0169 (0.113)			
Early social distancing				-0.0780 (0.072)		
Early school closure					0.0954 (0.177)	
Early shelter in place						0.0700 (0.073)
Covid-19 deaths per capita (logs)	0.1184*** (0.043)	0.1181** (0.044)	0.1169*** (0.044)	0.1089** (0.045)	0.1145*** (0.042)	0.1209*** (0.043)
Observations	51	51	51	51	51	51
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.260	0.257	0.256	0.273	0.264	0.270

Source: U.S. Department of Labor, U.S. Census Bureau, <https://covidtracking.com>, <https://github.com/Keystone-Strategy/covid19-intervention-data>.

Notes: The table reports the estimated coefficient of a regression which the total number of unemployment insurance claims per capita (in logs) is function of NPIs, the total number of COVID-19 death per capita, per capita GDP (in logs), the employment share in hotels and leisure, and a dummy for the presence of paid sick days laws, at the state level. The sample is a cross-section of 51 U.S. states, with variables measured from March 8 to April 25, 2020. The NPIs considered are: (i) social distancing, (ii) closure of nonessential services, (iii) closure of public venues, (iv) school closures, and (v) shelter-in-place orders. For each NPI, a state is considered an early adopter if the policy has been implemented within a week from the day in which the first death in the state has been recorded. A state is considered an early NPIs adopter if all these five policies have been implemented within a week from the day in which the first death in the state has been recorded. Results obtained excluding control variables are qualitatively and quantitatively similar.