RESEARCH

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

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This note provides a framework to use high-frequency indicators, such as electricity usage, for policymakers to assess the economic impact of COVID-19 in close to real time. Further, the note examines the link between economic activity and mitigation efforts to help policymakers better understand the possible path of economic activity as lockdown measures are relaxed. We find that:

(1) Electricity usage in Europe declined by 10–15 percent (more in harder-hit countries) during the acute phase of the pandemic—historically, a 1 percent drop in electricity usage has been associated with 1.3–1.9 percent drop in output.

(2) The decline in electricity usage and job losses in the U.S. are larger in states with a lower share of jobs that can be done from home. Further, job losses are larger in poorer states and in states that do not have in place laws for paid sick days.

(3) The heterogeneous impact of COVID-19 is mostly captured by changes in people's observed mobility, while, so far,

(4) there is no robust evidence of additional impact from the adoption of *de jure* non-pharmaceutical interventions such as school and business closures and shelter-in-place orders.

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I. HIGH-FREQUENCY INDICATORS: WHY AND HOW?

The COVID-19 pandemic is causing economic disruption at unprecedented speed and scale. For instance, thirty million Americans filed for unemployment in the past six weeks. It took about a year to reach that number in the wake of the Lehman Brothers' bankruptcy. Against this background, the relatively slow frequency of most macroeconomic indicators represents a challenge for policymakers tasked with mitigating the economic impact of the crisis and charting a way to the recovery phase.

High-frequency indicators, such as electricity usage, can complement traditional measures of economic activity in helping policymakers tailor their responses to "flatten the recession curve" (Gourinchas 2020). We exploit the variation in the timing and intensity of COVID-19 outbreak across different locations—and, hence, the policy-induced and/or voluntary changes in behavior. We use two proxies for the outbreaks: the number of COVID-19 cases or deaths and the Google Community Mobility index (Google, 2020). The latter measures the number of times individuals visit public places (transit stations, workplaces, retail stores and recreation places, and groceries and pharmacies) and thus captures mitigation efforts through reduced mobility. We investigate how economic conditions deteriorate across European countries and U.S. states as the outbreaks spread and/or people stay at home. Although we do not fully disentangle the direct effect of the pandemic from that of mitigation efforts and heightened uncertainty, we provide early evidence on the role of Non-Pharmaceutical Interventions (NPIs), such as school and business closures and shelter-in-place orders.

We measure economic conditions with electricity usage and unemployment insurance (UI) claims. Electricity is an input in most of economic activity and is difficult to substitute in the short run. Electricity usage is a very useful high-frequency indicator of economic fluctuations (Chen et al. 2019, Cicala 2020). UI claims are available at weekly frequency for all U.S. states and 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 (Wolfers 2020). We complement our analysis with data on hours worked from more than 100,000 local businesses from the time-tracking tool Homebase. These indicators are available with a short time lag, so they can be used to track economic activity as close as possible to "real time." We focus on these indicators rather than other high-frequency measures, 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.[2]

II. COVID-19 AND ECONOMIC ACTIVITY IN EUROPE

We compare current electricity usage to the same day of the same week in 2019 for 31 European countries.[3] Since early March, electricity usage has been declining in most countries, despite lower energy prices: electricity consumption was about 5 percent lower than in 2019 during weekdays in the median country in the sample (Figure 1). The decline has accelerated in April reaching 10–15 percent, and roughly twice this median value in Italy—the first European country to experience an extensive outbreak and one of the hardest-hit so far.

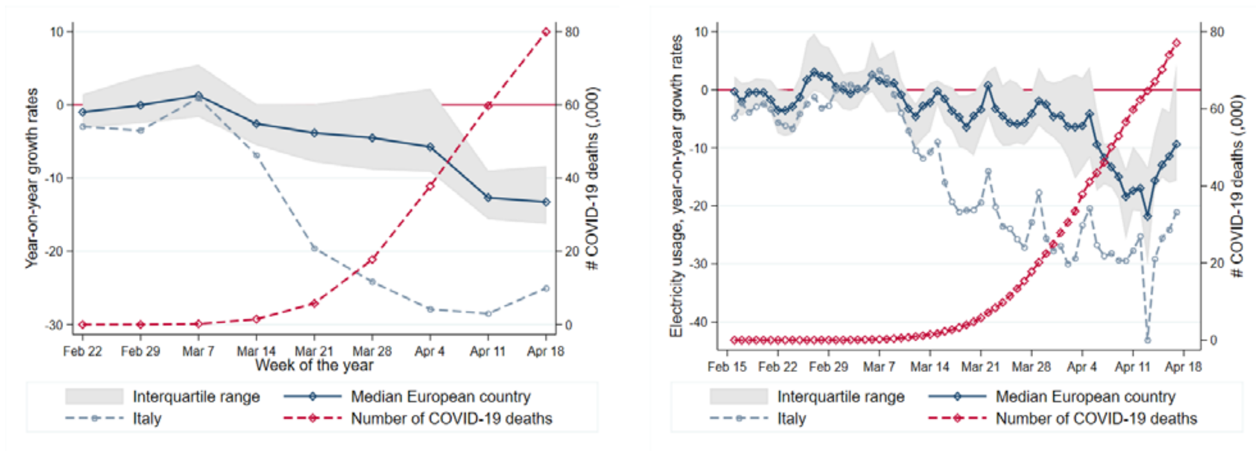
Cross-country analysis shows that countries with a more severe outbreak, as measured by deaths per capita, and a sharper decline in people's mobility have reduced their electricity consumption more (Figure 2). This result is robust to controlling for the share of manufacturing in national production and weather conditions. The estimated coefficient suggests that during the acute stage of the pandemic, a doubling of the COVID-19

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

[3] Since electricity usage exhibits substantial day-of-the-week fluctuations, we compare each day to the same day of the week in 2019. So, we compare electricity usage on Tuesday March 31, 2020, with that on Tuesday April 2, 2019 rather than Sunday March 31, 2019. We use daily data from ENTSO-E.

outbreak is associated with a decrease in electricity usage of approximately 2.4 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 pandemic.

FIGURE 1. COVID-19 and Electricity Usage in Europe: Time Series

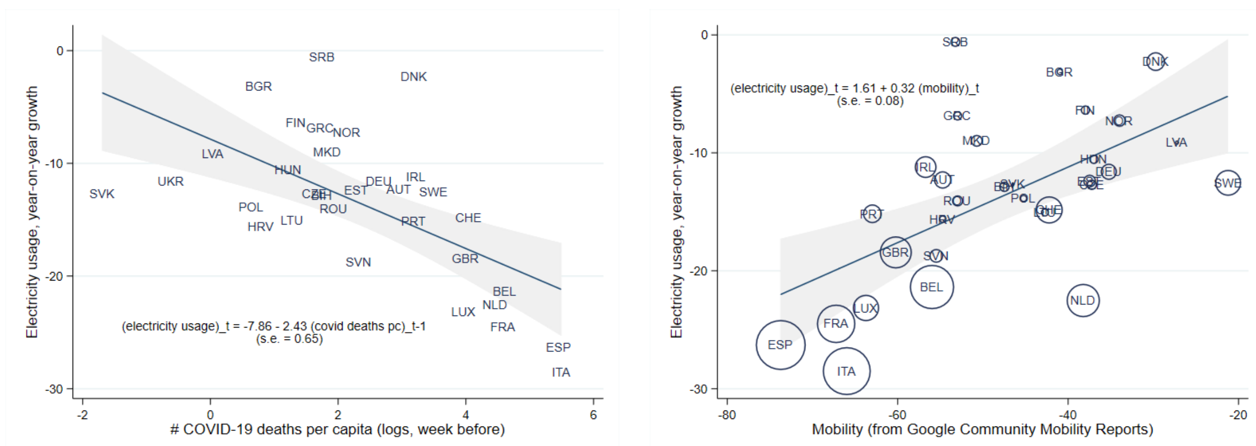


A. Weekly, weekdays only

B. Daily

Source: ENTSO-E, ECDC.
Note: The figure plots the relationship at weekly (panel A) or daily (panel B) frequency between the year-on-year change in electricity usage and the number of COVID-19 deaths across countries up to April 18. Panel A: change in electricity is defined as the year-on-year difference with respect to same week of the year in 2019. We exclude consumption during weekends and national holidays. To keep the number of working days within a week balanced between 2019 and 2020, when we exclude a holiday, we also exclude the same day of the same week of the previous/following year. Panel B: change in electricity is defined as the year-on-year difference with respect to the same day of the week and some week of the year of 2019. In most European countries Easter was celebrated on April 12 in 2020 and April 21 in 2019, which is the "equivalent" of April 19, 2020 on the same-day of the same-week scale. We partially correct for this by extending the weekend to the first day after Easter where it is a national holiday. We observe a drop of electricity usage in the days heading to Easter, perhaps because of vacations and business closures. Therefore, part of the drop observed in the days around April 12 (and the increase around April 19) is due to this Easter effect.

FIGURE 2. COVID-19 and Electricity Usage in Europe: Cross-Section



A. Electricity usage and COVID-19 deaths

B. Electricity usage and mobility

Source: ENTSO-E, ECDC, Google Community Mobility Reports.
Note: Panel A plots the percent change in daily electricity usage relative to the same day of the same week in 2019 and the number of COVID-19 deaths per capita in 32 continental 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. Bubble size corresponds to the number of COVID-19 deaths per capita. 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.

Policymakers could monitor electricity usage to gauge the economic impact of COVID-19.[4] For instance, 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,[5] 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 (Table 1). 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. These estimates are within the range of estimates from the literature (Stern 2018).[6]

TABLE 1. Electricity and Output

VARIABLES **(in delta log per capita)**		Electricity			GDP			Electricity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP	0.0801	0.2703***	0.2861***				0.7756**	0.5287*	0.5602**
	(0.101)	(0.068)	(0.063)				(0.333)	(0.279)	(0.271)
Banking crisis (t to t-2)				-0.0322***	-0.0374***	-0.0368***			
				(0.006)	(0.011)	(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			
R-squared	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).
Note: The table presents the results of running 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). 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.

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

In the United States, average daily electricity usage in early April was 5 percent lower than the same period in 2019. More strikingly, 30 million new unemployment insurance (UI) claims have been filed since the outbreak of the pandemic. Job losses are concentrated in states that have been hit harder by COVID-19 (Figure 3, panel A), in line with recent evidence shown for U.S. cities during the 1918 flu pandemic (Correia, Luck, and Verner 2020). Similar evidence is also discussed by Doerr and Gambacorta (2020), Coibion, Gorodnichenko, and Weber (2020) and Béland et al. (2020).[7]

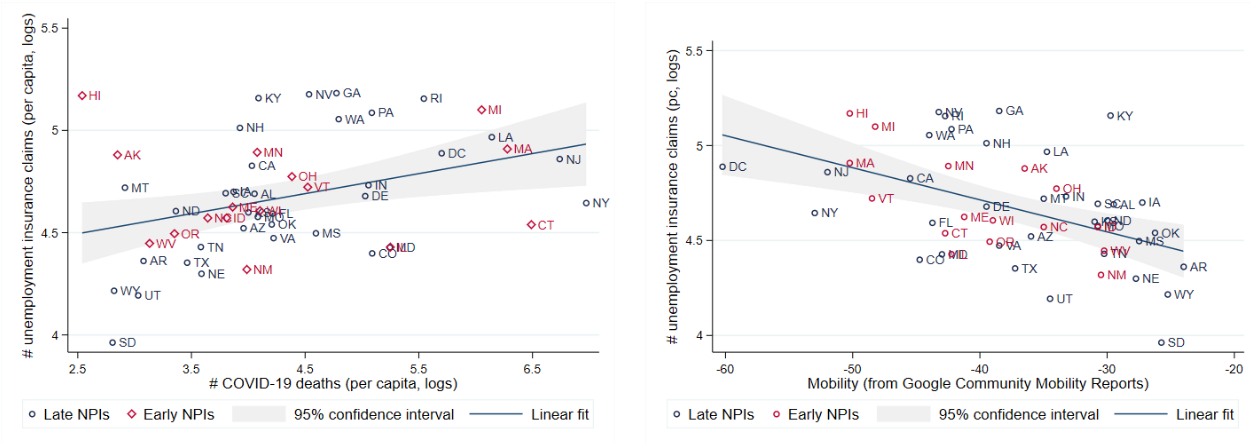
[4] Two caveats are in order: extrapolation from cross-sectional results to the aggregate (Nakamura and Steinsson 2018) and potential nonlinearities.

[5] These assumptions could be violated because electricity used at home may increase during the lockdown, or because other inputs are not as easy to adjust as energy. Also important to note that, post-COVID-19, we may be in a new normal where fewer people commute or go out and more work from home, which means the current elasticity could differ from the past.

[6] These numbers are estimated at the weekly level. Additional assumptions on the duration and intensity of the outbreak and mitigation measures are needed to estimate quarterly and annual GDP loss, which is outside the scope of this note. See Section V for additional caveats.

[7] 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.

FIGURE 3. COVID-19, NPIs, Mobility, and Unemployment Insurance Claims in the United States



A. UI claims and COVID-19 deaths

B. UI claims and mobility

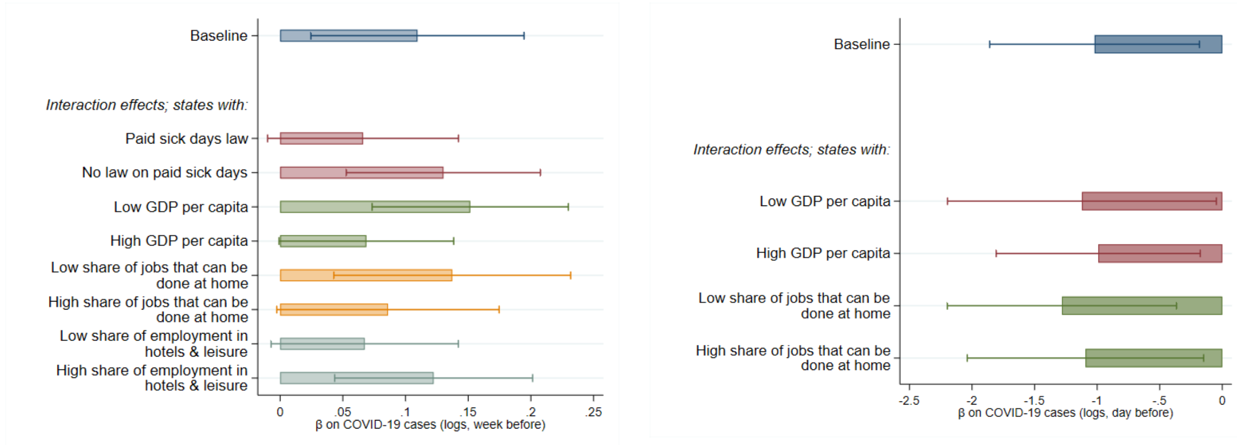
Source: US Department of Labor, US Census Bureau, https://covidtracking.com, https://github.com/Keystone-Strategy/covid19-intervention-data, Google Community Mobility Reports.
Note: Panel A plots the total number of unemployment insurance claims per capita (in logs) and the total number of COVID-19 deaths per capita, at the state level, from March 8 to April 25, 2020. The solid line plots a linear fit. The slope is 0.10 (s.e.=0.04). Panel B plots the total number of unemployment insurance claims per capita (in logs) 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, from March 8 to April 25, 2020. The solid line plots a linear fit. The slope is -0.017 (s.e.=0.004). 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.

Exploiting both the time and cross-sectional dimensions of the data, we see that as the number of COVID-19 cases increases, electricity usage decreases while UI claims increase. The results are economically significant. For electricity usage, the average elasticity is 0.009 for all U.S. continental states and 0.022 for the top 5 states with most COVID-19 cases, indicating that during the acute stage of pandemic, a doubling of the number of cases leads to a decrease in electricity usage of 0.9 percent among continental U.S. states and 2.2 percent among the top 5 states with most COVID-19 cases.[8] 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 has weakened over time—during March 7–21, the elasticity was close to 0.3—suggesting that the labor market has reacted very fast to the outbreak and the related social distancing measures.

The economic reaction is heterogenous across U.S. states, reflecting economic and institutional characteristics. For a given number of COVID-19 cases, UI claims increased more in poorer states, in states with a lower employment share in hotels and leisure, and lower share of jobs that can be done from home, and in states that do not have laws for paid sick days (Figure 4, panel A—these differences are statistically significant). The impact on electricity usage is also stronger among states with lower shares of jobs that can be done at home (Figure 4, panel B). These results are robust to controlling for the share of manufacturing in state economy and weather conditions.

[8] As with the cross-country regressions for Europe, there are likely nonlinearities involved.

FIGURE 4. COVID-19, Unemployment Insurance Claims, and Electricity Usage: Panel Regressions



A. COVID-19 and UI claims

B. COVID-19 and electricity usage

Source: US Department of Labor, US 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).
Note: Results of estimating equation: $y_{s,t} = \alpha_s + \gamma_t + \beta * COVID_{s,t-1} + \delta * X_s * COVID_{s,t} + \varepsilon_{s,t}$. S is a U.S. state, t is a week between March 7 and April 25, 2020 (Panel A) or a day between March 3 and April 4, 2020 (Panel B). $y_{s,t}$ is the number of unemployment insurance claims in a that week (in logs) (Panel A) or electricity usage (Panel B, in logs of MWHs, relative to the same day of the week of the same week in 2019), $COVID_{s,t-1}$ is the number of COVID-19 cases in the previous week (Panel A) or the day (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=7, n=51 (Panel A), or t=49, n=50 (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 as below the first quartile of the state distribution. Each bar also shows the associated 90 percent confidence intervals. Standard errors are clustered by state.

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

The positive association between COVID-19 cases or deaths and economic contraction can be explained by the extent and effectiveness of mitigation efforts—which we capture by changes in mobility relative to January 2020. This 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 the public. We find that mobility is positively associated with electricity usage (Figure 2, panel B) and negatively associates with the number on UI claims (Figure 3, panel B). In contrast, the relationship between *de jure* NPIs and economic contraction is weaker. The cross-sectional correlation between the 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. 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 2).

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.[9]

[9] 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).

TABLE 2. COVID-19, NPIs, and Unemployment Insurance (UI) Claims in the United States

Dependent variable: 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***	0.1181**	0.1169***	0.1089**	0.1145***	0.1209***
	(0.043)	(0.044)	(0.044)	(0.045)	(0.042)	(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: US Department of Labor, US Census Bureau, https://covidtracking.com, https://github.com/Keystone-Strategy/covid19-intervention-data.
Note: 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.

Furthermore, using daily data for a large sample of local businesses from Homebase (Bartik et al. 2020), 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).[10] 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 the 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 6). Moreover, the early NPIs—school closures in many cases—triggered the drop 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).

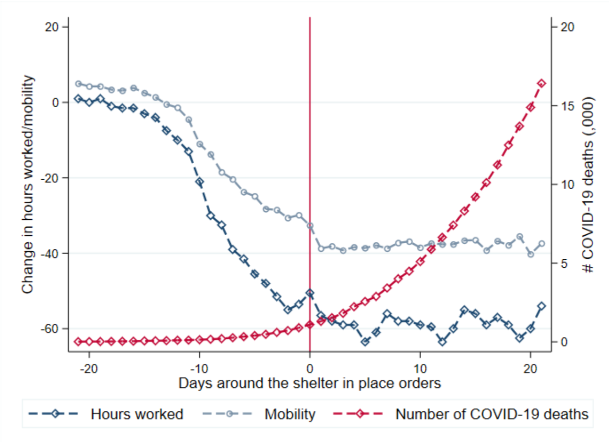
A likely explanation of this difference is that Americans "learnt" from the European experience and practiced voluntary distancing and closures before *de jure* NPIs were adopted. Increased news coverage on COVID-19 during the second week of March is also consistent with this increased "awareness" explanation: 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.

These findings suggest that avoiding or delaying NPIs may not fully shield an economy from the COVID-19 shock,[11] and that the depression of economic activity may persist even after mandatory lockdown measures are lifted if people continue to voluntarily limit their mobility.

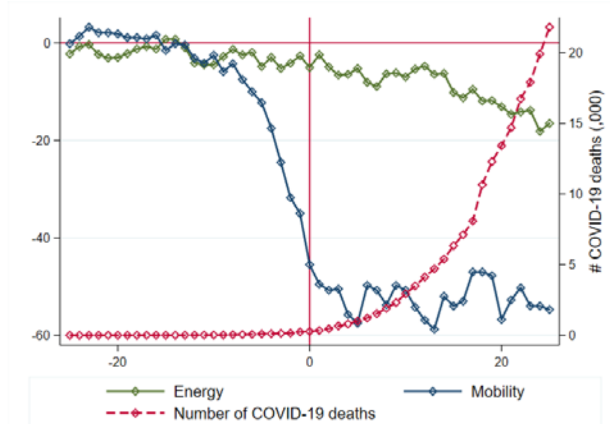
[10] Sectors that are hit harder and earlier by the pandemic, such as restaurants, may be overrepresented in this data source.

[11] 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).

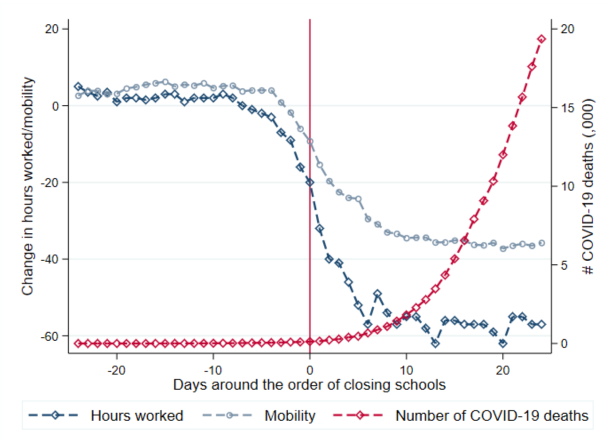
FIGURE 5. COVID-19, NPI Timing, Mobility, and Economic Activity



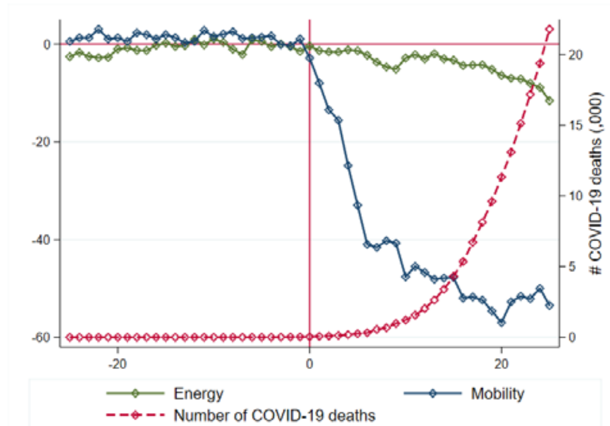
A. Shelter-in-place orders in the United States



B. Stay-at-home orders in Europe



C. School closures in the United States



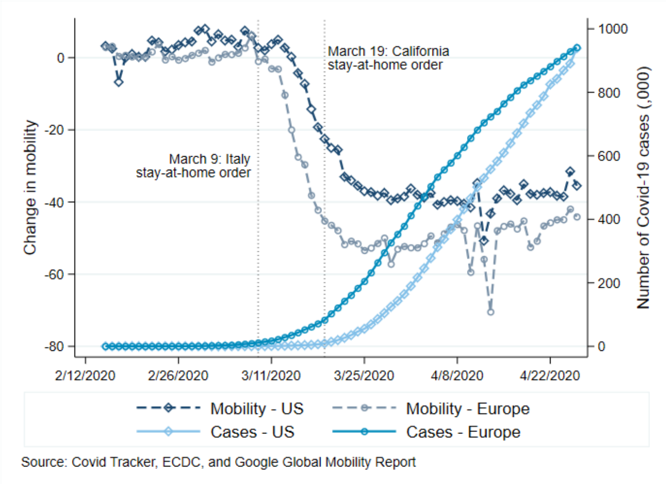
D. School closures in Europe

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

V. CAVEATS

The use of cases or death counts as a measure of the COVID-19 shock at the local level comes with a few caveats. The numbers of cases depend on testing policies and capabilities whereas the number of deaths depends on healthcare capacity and demographics. Importantly, the risk that cases and deaths are undercounted due to local protocols could be non-trivial. Moreover, 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.). The use of high-frequency indicators is also subject to several caveats. For instance, there are many elements besides economic conditions that affect electricity consumption, such as energy efficiency, electricity prices, and weather conditions. Also, measurement error may be present in mobility data.

FIGURE 6. COVID-19, NPI Timing, and Mobility in Europe versus the United States



Source: https://covidtracking.com, Google Community Mobility Reports, Homebase, ECDC, ENTSO-E.
Note 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.

V. KEY TAKEAWAYS

Our analysis relies on the heterogeneous timing and intensity of the COVID-19 outbreak across different European countries and U.S. states to provide some useful indications to guide policymaking.

First, the sharp decline in electricity usage and the unique 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. 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 sizable, 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, although COVID-19 is a truly global shock, regions and countries where the outbreak is more sizeable experience significantly more severe economic losses. This underlines the importance of preventions, early responses, and other health measures to contain the outbreak at the local and national level.

Third, the early 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, unless workers and consumers feel that the danger stemming from the epidemic is effectively under control. As countries start looking into reopening the economy, 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.

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