Policy Research Working Paper 9257

The Sooner, the Better

The Early Economic Impact of Non-Pharmaceutical Interventions during the COVID-19 Pandemic

Asli Demirgüç-Kunt
Michael Lokshin
Iván Torre

WORLD BANK GROUP
Europe and Central Asia Region
Office of the Chief Economist
May 2020

Policy Research Working Paper 9257

Abstract

The size of the economic shocks triggered by the COVID-19 pandemic and the effects of the associated non-pharmaceutical interventions have not been fully assessed, because the official economic indicators have not been published. This paper provides estimates of the economic impacts of the non-pharmaceutical interventions implemented by countries in Europe and Central Asia over the initial stages of the COVID-19 pandemic. The analysis relies on high-frequency proxies, such as daily electricity consumption, nitrogen dioxide emission, and mobility records, to trace the economic disruptions caused by the pandemic, and calibrates these measures to estimate magnitude of the economic impact. The results suggest that the non-pharmaceutical interventions led to about a decline of about 10 percent in economic activity across the region. On average, countries that implemented non-pharmaceutical interventions in the early stages of the pandemic appear to have better short-term economic outcomes and lower cumulative mortality, compared with countries that imposed non-pharmaceutical interventions during the later stages of the pandemic. In part, this is because the interventions have been less stringent. Moreover, there is evidence that COVID-19 mortality at the peak of the local outbreak has been lower in countries that acted earlier. In this sense, the results suggest that the sooner non-pharmaceutical interventions are implemented, the better are the economic and health outcomes.

This paper is a product of the Office of the Chief Economist, Europe and Central Asia Region. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at ademirguckunt@worldbank.org, mlokshin@worldbank.org, and itorre@worldbank.org.

The Sooner, the Better:
The Early Economic Impact of Non-Pharmaceutical Interventions during the COVID-19 Pandemic

Asli Demirgüç-Kunt, Michael Lokshin and Iván Torre*

Keywords: pandemic, COVID-19, economic impact, high-frequency data, Europe and Central Asia, non-pharmaceutical interventions.

JEL: D14, E21, G51

*The authors are at the World Bank. This paper's findings, interpretations, and conclusions are entirely those of the authors and do not necessarily represent the views of the World Bank, its Executive Directors, or the countries they represent. We thank Vladimir Kolchin and Sharanya Pillai for their excellent support.

1. Introduction

An outbreak of COVID-19, the disease caused by the SARS-Cov-2 coronavirus, was identified in Wuhan, China, in late December 2019. On January 23, 2020, the Chinese government implemented a very stringent lockdown of the city of Wuhan and the surrounding Hubei province, which was lifted only in staggered dates between March 13 and April 8. This extreme type of non-pharmaceutical intervention (NPI) became the standard approach adopted by governments of most countries as COVID-19 spread across the planet. By late March 2020, as much as 25% of the world population was under similar lockdown measures (Hale et al. 2020).

In the absence of a vaccine or a treatment, non-pharmaceutical interventions are an effective way to contain the disease. The spread of COVID-19 was suppressed by the lockdown of the Hubei province of China and the broader social distancing measures implemented in the rest of the country between January and March 2020. However, lockdowns are not the only NPIs that prevent the spread of the disease. The Republic of Korea; Taiwan, China; Vietnam; and Singapore, to a certain degree,[1] have managed to control the outbreaks with extensive testing and contact tracing. These countries, having been exposed to respiratory infectious diseases in the recent past, notably the SARS outbreak in 2002-03 and MERS in 2015, had developed the capacity to quickly ramp up testing and contact tracing by the time they detected the first cases of COVID-19 (Bali et al., 2020). Western countries were not well-prepared for the outbreak. Until now, noncommunicable diseases like cancer or heart disease represented most of the burden of disease in the West (Institute for Health Metrics and Evaluation, 2017). For most non-East Asian countries, the only available NPI that could contain the spread of COVID-19 was a lockdown. Only when massive testing capacity was developed -in record speed in many cases- did governments start considering the possibility of softening the lockdown and moving to milder NPIs.

The social distancing measures and especially lockdowns have a systemic impact on the economy. The closure of stores, restaurants, and businesses, and disruptions of the global value chains lead to direct losses of revenue, unprecedently high unemployment rates, and sharp declines in personal incomes. The impact of NPIs on economic activity has gradually moved to the forefront of public debate. In some countries, there are growing voices asking for an attenuation of the strictest types of NPIs, claiming that the economic downturn associated with them is more severe than the human cost these interventions are trying to prevent.

The objective of this paper is to contribute to the debate on the human and economic impact of the NPIs. We illustrate the economic impact of the different types of NPIs implemented by countries in Europe and

[1] After succesfully controlling the spread of the disease during January-March 2020, Singapore witnessed a brusque increase in infections in mid-April. The new cases were clustered in foreign workers dormitories and construction sites.

Central Asia over the initial stages of the COVID-19 pandemic. Given that standard measures of economic activity are produced with a delay and are yet not available, we rely on high-frequency proxies to trace the disruptions caused by the NPIs. These proxy measures are calibrated to provide an economic magnitude of the effects.

This paper proceeds as follows. The next section provides a short review of the relevant literature on pandemics. Section 3 describes data that can be used to provide a high-frequency estimation of economic activity. Section 4 discusses the evolution of the COVID-19 pandemic in Europe and the implementation of NPIs. Section 5 illustrates the impact of NPIs on the high-frequency activity measures and relates this to the evolution of the pandemic. In section 6, we provide estimates of the impact of NPIs and the stage of the pandemic on activity measures for countries in the region and discuss the calibration between these alternative measures and economic activity. The last section concludes with a discussion on policy implications.

2. Pandemics, NPIs and economic performance: a short review of the literature

The COVID-19 outbreak has triggered a large amount of scholarly work. Much of it builds upon earlier work on past pandemics, notably on the 1918 "Spanish Flu." Brainerd and Siegler (2003) find that in the United States, the states most affected by the pandemic had stronger per capita income growth over the following decade and argue that this was due to an increase in labor productivity as measured by a higher capital-labor ratio. Garrett (2009) shows that higher mortality in 1918 was associated with higher wage growth at the city and state levels from 1914 to 1919. Almond (2006) looks at the effect of *in utero* exposure to influenza on individual outcomes several decades later. He finds that a cohort *in utero* during the pandemic displayed worse education and health outcomes compared with other birth cohorts. Guimbeau, Menon, and Musacchio (2020) analyze human capital outcomes of the cohorts born during the 1918 pandemic in São Paulo, Brazil. They find adverse effects of higher exposure to the disease on both the short-term -as measured by infant mortality and sex ratios- and the long-term -literacy at age 20 – outcomes.

Some of the key questions about the impact of the 1918 pandemic have been revisited recently.[2] Barro, Ursua, and Weng (2020) look at the effect of influenza-related mortality in 43 countries and find that the pandemic lowered real GDP between 6 and 8 percent in the typical country. Velde (2020) analyzes high-frequency data from the United States and finds that, in the short term, the recession triggered by the pandemic was sharp but short. Correia, Luck, and Verner (2020) demonstrate that cities in the United States that had higher mortality rates during the pandemic eventually had worse economic outcomes over the

[2] Also see the recent work of Jordà, Singh and Taylor (2020) on the long-run consequences of historical pandemics dating back to the 14th century.

following five years as measured by growth in manufacturing employment. They also observe a similar negative impact on economic performance at the state level. Their work also discusses the role played by non-pharmaceutical interventions - until recently, only a topic of interest of epidemiologists. In line with the epidemiological literature, Correia, Luck, and Verner show that cities that implemented NPIs earlier on and for a longer time saw lower mortality peaks and cumulative mortality. Moreover, speedier, stricter, and longer NPIs were associated with better economic outcomes in the long run.

The relationship between health and economic outcomes of a pandemic is at the heart of scholarly work today, and one of the major subjects of discussion has been the role played by supply and demand forces. On the one hand, a pandemic may generate a negative supply shock simply by making workers sick and lower their productivity – and there is anecdotal evidence that, indeed, this was a major source of business disruption during the 1918 Flu.[3] On the other hand, consumers may react to the pandemic by cutting down on "social" consumption or any type of consumption that requires interpersonal contact (Wren-Lewis, 2020). Similarly, bleak economic prospects may depress private investment. Both of these effects can be characterized as demand shocks. However, government-mandated NPIs can be seen as shocks to both supply and demand, as they force workers to stay at home and prevent the consumption of certain services. In this line, Guerrieri et al. (2020) model the lockdown/social distancing effect triggered by a pandemic as a "Keynesian" supply shock, which ends up generating a drop in aggregate demand larger than the supply shock itself.

In this context, the economic effect associated with NPIs has caught particular attention in the public debate because, in contrast to the 1918 Flu pandemic, governments have been implementing more drastic measures to contain the outbreak.[4] These interventions can create a serious economic downturn (Gourinchas, 2020). Eichenbaum, Rebelo and Trabandt (2020) extend a canonical epidemiological model to include the interaction between economic decisions and epidemics and find that the best containment policy can save a large number of lives but may induce a more severe recession than without the containment. However, Acemoglu et al. (2020) carry out a similar exercise and show that targeted policies that are combined with measures that reduce interactions between groups and increase testing and isolation of the infected can minimize both economic losses and deaths. Similarly, Aum, Lee and Shin (2020) calibrate a model to the progression of the pandemic in Korea and the United Kingdom and find that aggressive testing and tracking

[3] Newspaper evidence from the 1918 pandemic in the United States, collected by Correia, Luck and Verner (2020), shows that workers calling sick disrupted production in many manufacturing plants. Velde (2020) finds that sizeable labor shortages affected the coal industry and caused drops of up to 20% in capacity utilization during the peak of the pandemic.

[4] As Correia, Luck and Verner (2020) note, the 1918 type of NPIs never reached the point of shutting down non-essential businesses. At most, staggered business hours were introduced to avoid crowding.

policies can reduce both the economic and health costs of COVID-19. In this sense, a lives-livelihoods trade-off in the short run[5] may not exist if targeted policies are feasible. Chang and Velasco (2020) highlight the endogeneity of that potential trade-off by pointing out that the economic policy responses to the pandemic may also affect the evolution of the pandemic, as individuals' compliance with public health directives depends in part on economic incentives.

In sum, while theoretical work on the current COVID-19 pandemic is abundant, still comparatively little is understood of its empirical consequences, partly due to its ongoing and rapidly evolving nature. The size of the economic shock triggered by the pandemic and the associated NPIs has not been fully assessed because the official economic indicators have not been published yet. And most importantly for the academic and policy debate, it remains to be seen whether the NPIs implemented in 2020 reduce both mortality and improve economic outcomes just as they did in 1918, as found by Correia, Luck and Verner (2020), and how these interventions interact with the supply and demand shocks triggered by the pandemic.

3. Measures of economic activity and data

The use of non-monetary measures as a proxy for economic growth has gained the attention of economists in recent years. Nighttime lights visible from space have been used to measure output growth,[6] but corrected measurements for recent periods are currently not available.[7] so they are not fit for the purpose of our study given that the pandemic-induced variability cannot be assessed.

Electricity is required by most economic activities. For many countries, electricity data are available with a daily lag and on a sub-regional level, providing an almost real-time picture of economic changes. The analysis of electricity usage in the United States during the Global Financial Crisis of 2008 allowed assessing the extent of recession several months before the official data were available. That is why electricity demand and use have been used as a relevant proxy for economic activity, either for high-frequency estimates or as a validation of standard measures of economic activity.[8] Cicala (2020)

---

[5] An issue that is seldom discussed is whether severe recessions may also have negative health outcomes in the long run. Douglas and Mazumder (2011) show that reduced food consumption during pregnancy (as proxied by fasting during Ramadan among the Muslim population) leads to higher adult disability rates. In this sense, economic distress among the poorest may affect their long-term health outcomes.

[6] See the work of Chen and Nordhaus (2011) and Henderston, Storeygard and Weil (2012). These authors use nighttime lights to estimate income growth in developing countries with low-quality statistical systems.

[7] Corrected nighttime lights measures for year 2020 will be published only at the end of this year. See https://earthdata.nasa.gov/learn/articles/feature-articles/nighttime-images-wuhan.

[8] Morris and Zhang (2019) argue that when data tampering is suspected, electricity figures can be also misreported. They cite the conflicting evidence from China raised by Fernald et al. (2013) and Koech and Wang (2012). As noted by Henderson, Storeygard and Weil (2012), a separate analysis done by the IMF (2006) for the case of Jamaica during the 1990s concluded that GDP growth in that country had been underestimated by official statistics by comparing it with the evolution of electricity consumption, which had been notably higher.

demonstrates that, in the short-run, changes in electricity consumption track standard economic indicators almost perfectly. Coincident economic activity indexes, used to provide estimates of economic activity before national accounts are published, usually include electricity consumption or production as one of the main input variables. A recently developed weekly economic index for the United States by Lewis, Mertens, and Stock (2020) includes electricity output as one of the input series.

Morris and Zhang (2019) propose using satellite readings of tropospheric NO_2 (nitrogen dioxide) densities as a proxy measure for economic activity. NO_2 is a byproduct of the combustion of fossil fuels and, therefore, directly indicative of economic activity.[9] NO_2 densities are available in a resolution that allows for sub-national analysis and also at the monthly and weekly levels. Morris and Zhang use variation in NO_2 densities to validate quarterly economic output data from China. They find evidence that official data on the output growth for some Chinese provinces differ significantly from what is implied from the observed variation in nitrogen dioxide densities.

Because the mobility restrictions are one of the main channels through which NPIs affect economic activity, any measure of mobility can be used as a measure of NPI enforcement or effective stringency. Location data derived from smartphones have become a popular way to illustrate mobility patterns by urban planners and transportation specialists.[10] In the context of the COVID-19 outbreak, Fang, Wang, and Yang (2020) study the impact that the lockdown of Wuhan and Hubei province had on the spread of the disease using mobility patterns derived from the use of the smartphone mapping app of Baidu, China's most popular search engine.

In our analysis, we use five data sets, the first two covering proxy measures of economic activity, and the remaining covering information on mobility, NPIs, and the evolution of the pandemic:

1) Electricity consumption. Data are presented as the total daily consumption in megawatts and were obtained from ENTSO-E for countries in the Baltic, Continental Europe, Ireland, Nordic, and UK synchronous grid areas, and from national grid operators for countries in other areas. Data are available for 37 counties in Europe and Central Asia; the period covered is January 1, 2017 to April 17, 2020.
2) NO_2 emissions (tropospheric vertical column densities, or VCD) obtained from the Ozone Monitoring Instrument (OMI) on NASA's Aura satellite. The data are presented at the daily frequency for all the world in pixels of 0.25 degrees of longitude x 0.25 degrees of latitude. The

[9] Some nonanthropogenic sources of nitrogen dioxide also exist. Soil burning of natural origins is one example. Estimates of purely anthropogenic emissions of nitrogen oxides (NOx) are only possible through modeling.
[10] See for instance Calabrese et al. (2013) and Hawelka et al. (2014) for an example of cellphone data used to track individual mobility patterns at the urban and global level respectively.

mean NO_2 VCD value is computed for all pixels corresponding to the surface of a country and, given variability due to weather and other factors, the 30-day moving average is used as the main variable of interest; the period covered is January 1, 2018 to April 17, 2020. We also use NO_2 emissions at ground level for 207 cities in 24 countries of Europe and Central Asia, collected by the World Air Quality Index project. The data consist of daily measurements of NO_2 and other emissions by stations located in different cities of the world.

3) Mobility trends data produced by Apple as derived from the requests for directions using Apple Maps are available for 33 countries in Europe and Central Asia. The trends data distinguish mobility by types – driving and walking. The period covered is January 13, 2020 to April 21, 2020.
4) Data on the implementation of non-pharmaceutical interventions from the Oxford Government Response Tracker, World Bank Education Global Practice COVID-19 dashboard, and alternative news sources.
5) Data on daily infections and deaths from COVID-19, by country, from Our World in Data, which are sourced from the European Centre for Disease Prevention and Control (ECDC). The period covered is January 1, 2020 to April 27, 2020.

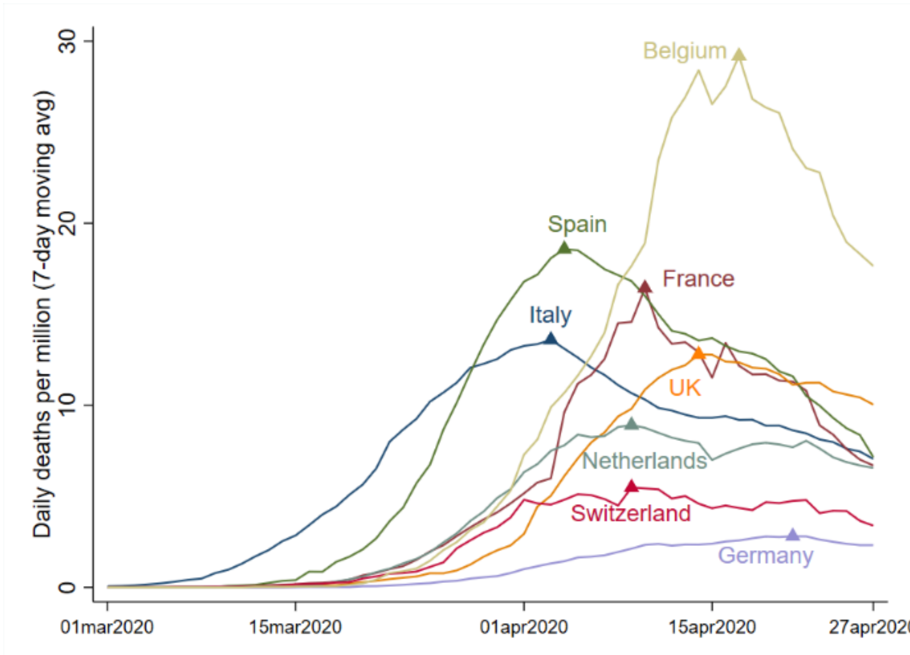
Table A.1 in the Appendix presents the indicator coverage for the mobility, electricity, and NO_2 data sets for countries of Europe and Central Asia. Data on NPIs and infection and death rates are available for all countries. Appendix 2 details the definition of the implementation dates for each type of NPI that is used in this paper: cancelation of public events, school closure, partial lockdown, and full lockdown.

4. The evolution of the COVID-19 pandemic and the implementation of NPIs in Europe

The first case of COVID-19 in Europe was reported in France on January 24, 2020. For the following weeks, reported cases were few and related to travelers coming from East Asia. On February 19, a case of a man who had no known travel to at-risk countries was reported in the region of Lombardy in Northern Italy. On February 22, the first death by COVID-19 was reported in the neighboring region of Veneto, signaling the presence of widespread community circulation of the virus in Northern Italy. In the days that followed, the infection cases and deaths by COVID-19 in Northern Italy saw exponential growth. Spain witnessed a similar outbreak with infection growing rapidly in Madrid, the Basque Country and La Rioja, and later in Catalonia. The pandemic spread to Belgium and France, and later to the Netherlands, Switzerland, and the United Kingdom.

Figure 1 shows the daily death rate per million for the first eight countries in Europe, which exceeded 10 deaths by COVID-19. By mid-April, these eight countries had already passed the peak number of daily deaths. Italy, Spain, France, Belgium, and the United Kingdom experienced steeper peaks, while Germany, the Netherlands, and Switzerland seem to have had a flatter curve. The timing of the implementation of NPIs, which we discuss later in this section, may be partly responsible for these differences.

Figure 1 – Evolution of COVID-19 pandemic in the first countries with widespread outbreaks

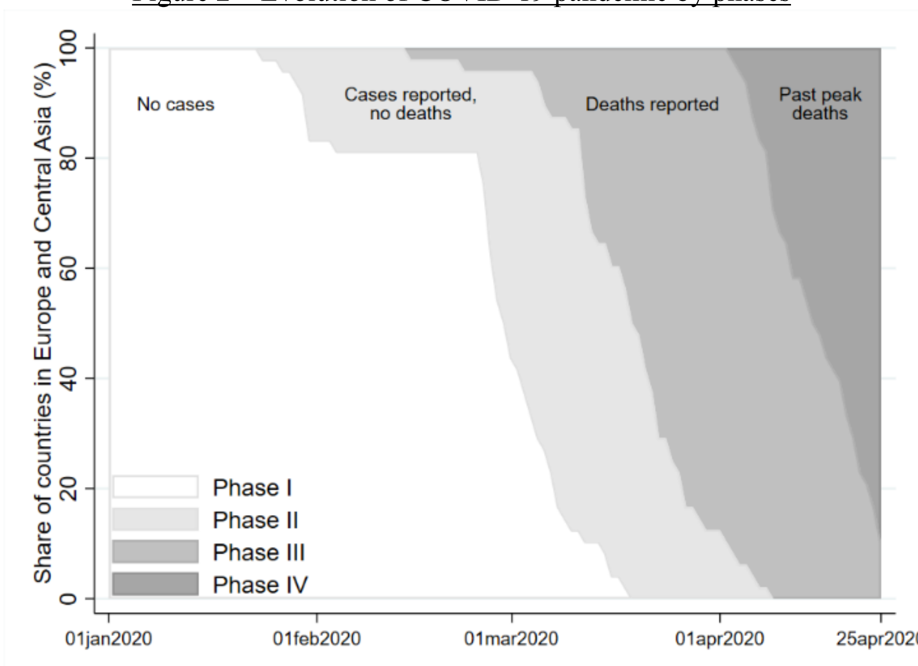


Note: this graph plots the 7-day moving average of daily deaths by COVID-19 per million inhabitants for the first eight countries in Europe, which reported ten deaths. The triangles indicate the peak number of daily deaths.

After the outbreak in Western Europe, COVID-19 spread throughout the rest of the continent. Northern Europe and Central and Eastern Europe reported their first cases in early March 2020. By the end of March, almost all countries in the region had passed the thresholds of 1,000 cases and 100 deaths. In the Western Balkans, every country had reported at least one death by April 1. Moldova, Turkey, and Ukraine registered their first deaths by COVID-19 on March 19. The Russian Federation and countries in Central Asia and the Southern Caucasus reported their first death between March 27 and April 3. Overall, by April 21, 2020, there were more than one million cases of COVID-19 infection reported in Europe and Central Asia, and more than 100,000 people had died from COVID-19. However, the real numbers of cases and deaths may be underestimated, as there is evidence of a large unexplained excess mortality in the countries most affected by the pandemic (EuroMOMO, 2020).

We represent the evolution of the pandemic at the country level in four phases: in the first phase (I), no cases are reported in the country. In the second phase (II), infection cases are reported, but no deaths. In the third phase (III), deaths are reported, and the number of daily deaths increases until it peaks. The fourth phase (IV) starts after the peak in daily deaths is reached, and the daily number of deceased starts decreasing. Figure 2 plots the share of countries in the region in each phase by date. In February 2020, most countries were in phase I and only a handful in phase II. By mid-March, all countries were either in phase II or phase III. In early April, some countries started moving into phase IV, and by mid-April, more than half of them had already passed the peak of daily deaths. For this last set of countries, the average daily deaths at the peak was 3.73 deaths per million – although with a high variance, from a minimum of 0.02 deaths per million to a maximum of 29.19 deaths per million, with the median at 1.37 deaths per million.

Figure 2 – Evolution of COVID-19 pandemic by phases



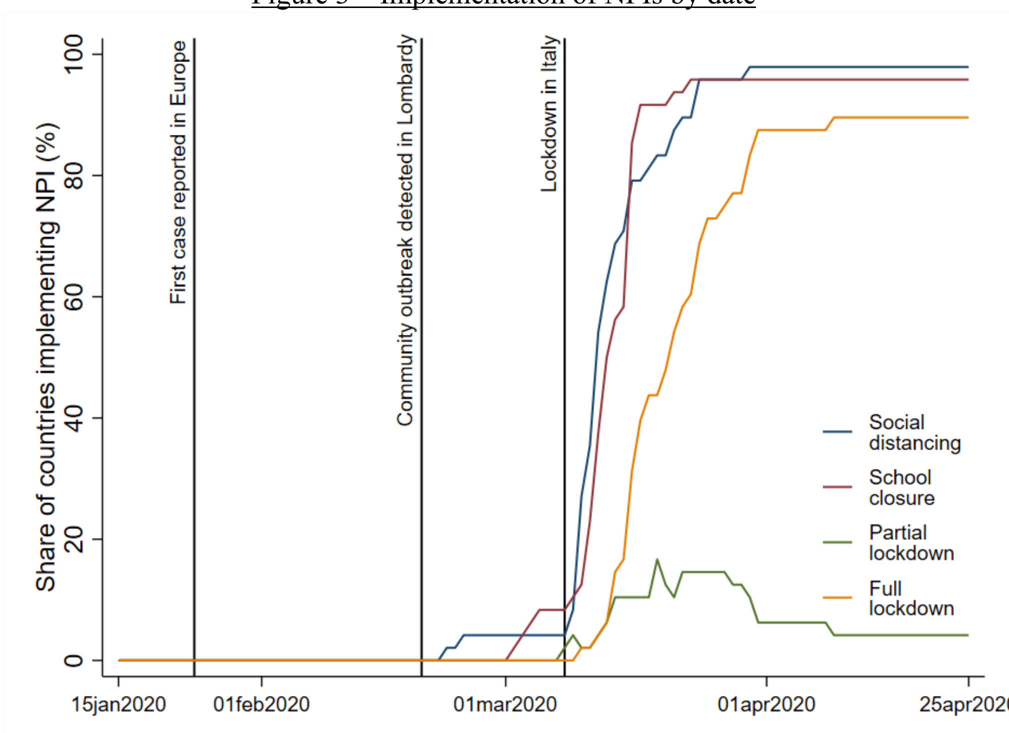
Note: this graph plots the share of countries in Europe and Central Asia in each phase of the local COVID-19 outbreak at each date between January 1 and April 25, 2020. Phase I corresponds to the period where no cases where reported in the country. Phase II corresponds to the period where cases of COVID-19 were reported, but no deaths caused by the disease. Phase III corresponds to the period where deaths by COVID-19 are reported, and the daily figure is regularly increasing. Phase IV corresponds to the period where the peak of daily deaths by COVID-19 has passed. The peak of daily deaths is determined as the highest 7-day moving average of daily deaths

As mentioned before, in the absence of extensive testing and tracing, NPIs are the sole tool available to limit the spread of COVID-19. Around the end of January 2020, countries in Europe imposed restrictions on travel originating in East Asia; no wide-ranging NPIs were implemented at that time. Figure 3 plots the share of countries in the region that implemented the four types of non-pharmaceutical interventions we analyze in this paper: 1) broad social distancing measures, as captured by the cancelation of public events and large gatherings; 2) the closure of schools; 3) the implementation of partial or targeted lockdowns; and

4) the implementation of full or general lockdowns. Appendix 2 details how the implementation date of each of these NPIs is defined.

The first trigger appears to have been the detection of the community outbreak in Lombardy. After the Italian government established a "red zone" forbidding entry and exit out of two clusters of towns in the regions of Lombardy and Veneto on February 23, other countries started implementing social distancing measures, and a few decided to close schools. Only after the Italian government went for a full lockdown, first in Lombardy on March 8 and in the whole country on March 10, the NPIs started being widely implemented in the region. Broad social distancing measures were in place in more than half of the European countries by March 12, and half of the countries had closed schools by March 13. Partial lockdowns were enforced in some countries, to be quickly replaced by full lockdowns. Half of the region was under complete lockdown by March 21. By April 9, all countries of Europe except Belarus, Sweden, Tajikistan, Turkey, and Turkmenistan were in full lockdown.

Figure 3 – Implementation of NPIs by date



Note: this graph plots the share of countries in Europe and Central Asia adopting each type of non-pharmaceutical intervention at each date between January 1 and April 25, 2020. Social distancing is defined as the canceling of public events and large gatherings. A partial lockdown only applies to a geographical region or a targeted set of activities.

Countries implemented NPIs at different phases of their local outbreaks. Table 1 indicates the phase each country's outbreak was in at the time of implementing each type of NPI. The lightest type of NPI -broad social distancing- was implemented mostly in the first two phases of the pandemic, with only a quarter of the countries implementing it after deaths by COVID-19 were locally reported. A similar timing pattern is present for school closures. Interestingly, about half of the countries enforced full lockdowns, the strictest intervention, before any death was locally reported. All these countries are outside Western Europe, suggesting that the human toll caused by the disease early on in that region may have driven authorities in the rest of Europe to take decisive measures early on to prevent a similar outcome.

Table 1 – Implementation of NPI and local COVID-19 outbreak phase

	Phases of the local outbreak at the time of implementation			
Type of NPI	I (No cases)	II (Cases but no deaths)	III (Deaths reported)	IV (Past peak daily deaths)
Ban of public events	15.8% (6)	63.1% (24)	21.1% (8)	0
School closure	13.0% (6)	65.2% (30)	21.7% (10)	0
Partial lockdown	5.9% (1)	64.7% (11)	29.4% (5)	0
Full lockdown	0	44.1% (19)	55.8% (24)	0

Note: the value in parentheses indicates the absolute number of countries in each cell. The percentages are calculated with respect to the total number of countries which implemented each type of NPI. Social distancing is defined as the canceling of public events and large gatherings. A partial lockdown only applies to a geographical region or a targeted set of activities

It is still early to fully understand the relationship between the timing of the NPIs and health outcomes because, in some countries, the peak has not been reached. But within the sample where the peak of daily deaths has already passed (43 countries as of April 25, 2020), the evidence shows that the level of the peak -an indication of how flat or how "spiked" the epidemic curve is- was lower for those countries that implemented NPIs early on than for those that implemented them at later stages of the outbreak.

Table 2 indicates the mean value of the peak for the countries that implemented each NPI by the phase of the local outbreak. Countries that implemented a full lockdown before any deaths were reported had a mean peak of about 0.8 daily deaths per million. Countries that imposed a full lockdown after deaths were reported had a peak more than six times higher at 6.29 daily deaths per million. A similar ratio of magnitudes is found for the remaining types of NPIs. Note that this table does not intend to provide an estimate of the effectiveness of each type of NPI because countries have adopted more than one of them simultaneously, precluding the possibility of estimating such direct effects. However, it provides suggestive evidence that the curve appears to have been "flatter" in those countries where NPIs were implemented on earlier stages of the pandemic.

Table 2 – Timing of NPI implementation and daily deaths at the epidemic peak

	Phases of the local outbreak at the time of implementation			
Type of NPI	I (No cases)	II (Cases but no deaths)	III (Deaths reported)	IV (Past peak daily deaths)
	Mean (*median*) daily deaths per million at peak			
Ban of public events	1.19	2.75	11.22	-
	0.32	*1.49*	*10.85*	
School closure	0.41	1.16	11.75	-
	0.44	*0.95*	*10.85*	
Partial lockdown	-	1.05	6.22	-
		0.84	*3.11*	
Full lockdown	-	0.79	6.29	-
		0.85	*2.81*	

Note: this table presents the mean daily deaths per million (7-day moving average) at the peak of the local COVID-19 outbreak for the countries in each cell. The median value is indicated in italics. Values in this table are calculated with information from the 43 countries which had passed the peak by April 25, 2020. Social distancing is defined as the canceling of public events and large gatherings. A partial lockdown only applies to a geographical region or a targeted set of activities.

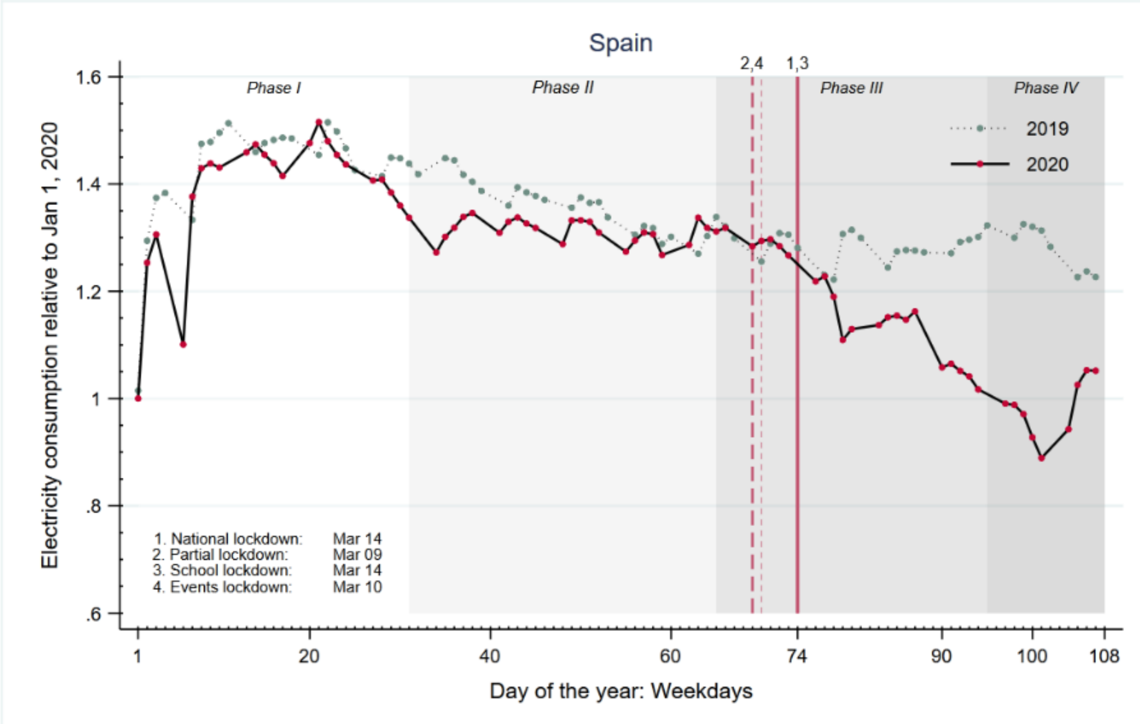
5. The impact of NPIs on mobility, electricity consumption, and NO_2 emissions

In this section, we analyze the impact of non-pharmaceutical interventions on human activity throughout Europe and Central Asia. We start by presenting a series of descriptive results that show the impact of the COVID-19 pandemic and the NPI responses on electricity consumption, NO_2 emissions, and mobility. We then provide cross-country illustration of the relationship between the implementation of NPIs and those variables, and we carry out a panel analysis to estimate the magnitudes.

5.1 Electricity consumption

Most economic activities require electricity. The changes in daily electricity consumption could be used to monitor the economic impact of the pandemic in real-time (Cicala 2020). The NPIs implemented in countries of Europe resulted in closures of stores, restaurants, many office buildings, and a reduction in electricity-intensive production. In the United States, grid operators have recently observed reduced weekday electricity demand relative to what is expected for this time of the year and weather conditions (EIA, 2020). Similar patterns are observed for countries in Europe and Central Asia.

Figure 4 – Electricity consumption by day of the year in Spain.

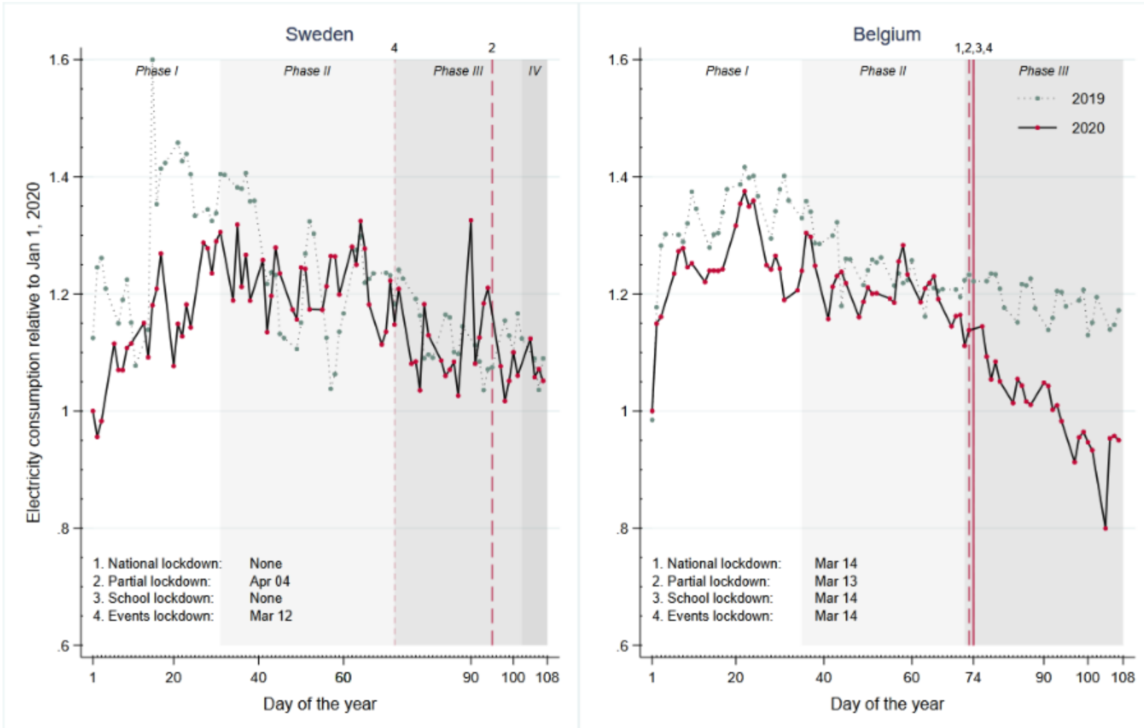


Note: this graph plots the daily consumption of electricity (grid electricity total load) for weekdays (weekends excluded) in the period between January 1 and April 17 of the year 2019 (dotted line) and 2020 (solid line) in Spain. Values are normalized by electricity consumption on January 1th, 2020. Phase I identifies the period with no detected cases of COVID-19; Phase II starts from the day when the first case is reported; Phase III begins at the date of the first death from the disease; Phase IV identifies the period after the peak of daily deaths in the country has been reached.

Figure 4 shows the changes in the consumption of electricity (grid electricity load) for Spain for the period from January 1 until April 17 for 2020 (solid line) and 2019 (dash line). On the onset of the pandemic in February 2020, the use of electricity in Spain was already lower compared to the same period in 2019.[11] The introduction of NPIs in early March 2020 resulted in further decline. Spain consumed about 30% less electricity in April 2020 compared to April 2019. An uptick in electricity consumption in mid-April most likely reflects the Government of Spain's decision to ease some of the lockdown restrictions.

[11] Some of the differences in the electricity consumption could be explain by the warmer weather in February 2020 compared to the same month last year (NOAA 2020) https://www.ncdc.noaa.gov/sotc/global-regions/202002.

Figure 5 – Electricity consumption by day of the year in Sweden and Belgium



Note: these graphs plot the daily consumption of electricity (grid electricity total load) for weekdays (weekends excluded) in the period between January 1 and April 17 of the year 2019 (dotted line) and 2020 (solid line) in Sweden (left panel) and Belgium (right panel). Values are normalized for each country by electricity consumption on January 1th, 2020. Phase I identifies the period with no detected cases of COVID-19; Phase II starts from the day when the first case is reported; Phase III begins at the date of the first death from the disease; Phase IV identifies the period after the peak of daily deaths in the country has been reached.

Figure 5 shows the trends in electricity consumption for Sweden and Belgium. The 2020 and 2019 lines are very close in Sweden, where no national lockdown measures were implemented. This reflects a small impact of the pandemic on economic activity in Sweden. On the other hand, Belgium introduced a whole range of social distancing measures on March 14, 2020, which had an immediate impact on economic activity in the country. In essence, electricity consumption has been declining sharply from the date of the national lockdown and dropped by about 30 percent relative to the same period in 2019.

Table 3 shows the average weekly electricity consumption level by the phases of the pandemic for countries in Europe and Central Asia. The patterns of electricity consumption of many countries in the region are similar to those of Spain and Belgium. Italy experienced one of the largest drops, at almost 30 percent. Significant declines in electricity consumption were registered in France, Latvia, and Poland.

Table 3 – Changes in electricity consumption by phases of local COVID-19 outbreak

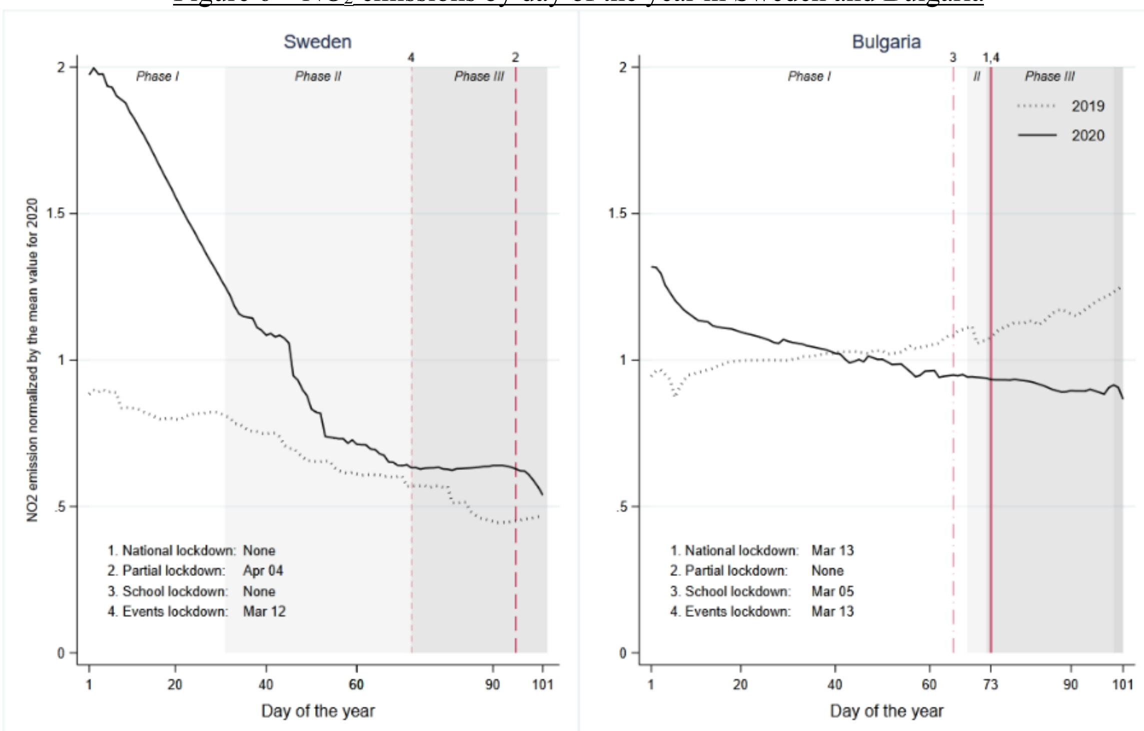
Country	**2019**			**2020**		
	Week of Phase II	*Week of Phase III*	*Week of Phase IV*	*Phase II*	*Phase III*	*Phase IV*
Austria	1.21	1.23	1.10	1.21	1.16	0.92
Belgium	1.32	1.17	.	1.18	1.09	.
B&H	0.92	0.97	1.00	0.88	0.90	0.84
Bulgaria	0.98	1.02	0.97	1.03	1.00	0.88
Croatia	1.10	1.04	.	1.11	1.03	.
Czech Republic	1.29	1.27	.	1.36	1.24	.
Denmark	1.14	1.18	1.11	1.24	1.21	1.01
Estonia	1.27	1.16	1.16	1.29	1.13	1.03
Finland	1.29	1.07	.	0.96	1.04	.
France	1.23	1.08	0.93	1.15	1.02	0.67
Georgia	1.13	1.05	0.92	1.08	0.96	0.94
Germany	1.44	1.34	.	1.39	1.34	.
Greece	1.11	1.05	1.00	0.98	0.96	0.97
Hungary	1.21	1.19	.	1.27	1.23	.
Ireland	1.15	1.15	.	1.22	1.17	.
Italy	1.70	1.59	1.47	1.51	1.50	1.07
Latvia	1.28	1.17	1.21	1.25	1.13	1.06
Lithuania	1.24	1.19	1.19	1.23	1.13	0.98
Moldova	1.28	1.18	1.14	1.09	1.11	0.98
Montenegro	0.65	0.64	.	0.89	0.78	.
Netherlands	1.03	1.04	0.93	1.12	1.10	0.71
N. Macedonia	0.91	0.77	0.78	0.82	0.82	0.67
Norway	1.02	1.10	.	1.16	1.00	.
Poland	1.33	1.34	1.30	1.35	1.30	1.04
Portugal	1.14	1.14	.	1.21	1.08	.
Romania	1.27	1.18	.	1.22	1.14	.
Russian Federation	1.15	1.02	.	1.11	1.00	.
Slovak Republic	1.19	1.15	.	1.22	1.03	.
Slovenia	1.29	1.32	1.34	1.34	1.20	1.03
Spain	1.39	1.25	1.26	1.28	1.26	0.99
Sweden	1.38	1.19	1.10	1.26	1.14	1.07
Switzerland	1.12	1.15	1.02	1.10	1.04	1.00
Turkey	1.14	1.10	.	1.15	1.14	.
Ukraine	1.17	1.15	.	1.04	1.02	.
United Kingdom	1.22	1.12	.	1.08	1.11	.

Note: this table plots the average value of electricity consumption (grid electricity total load) for the week of the year when the first case of COVID-19 infection was reported in 2020 (phase II), for the week when the first death by COVID-19 was reported in 2020 (phase III), and for the week when the peak of daily deaths was reached in 2020 (phase IV). Empty cells indicate that the peak of daily deaths for that country had not been reached as of April 17, 2020. The values are normalized for each country by the electricity consumption registered on January 1, 2020

5.2 NO_2 emissions

Nitrogen dioxide (NO_2) emissions are closely correlated with traffic, construction activities, industry, and coal-fired power plants. The NPI measures and especially national lockdowns imposed on the populations of most European countries resulted in a sharp drop in commute and overall mobility and halt of many industrial activities. The reduction of NO_2 emissions can be registered via satellite images and could potentially be used as a proxy for the economic impact of the pandemic (World Bank, 2020).

Figure 6 – NO_2 emissions by day of the year in Sweden and Bulgaria

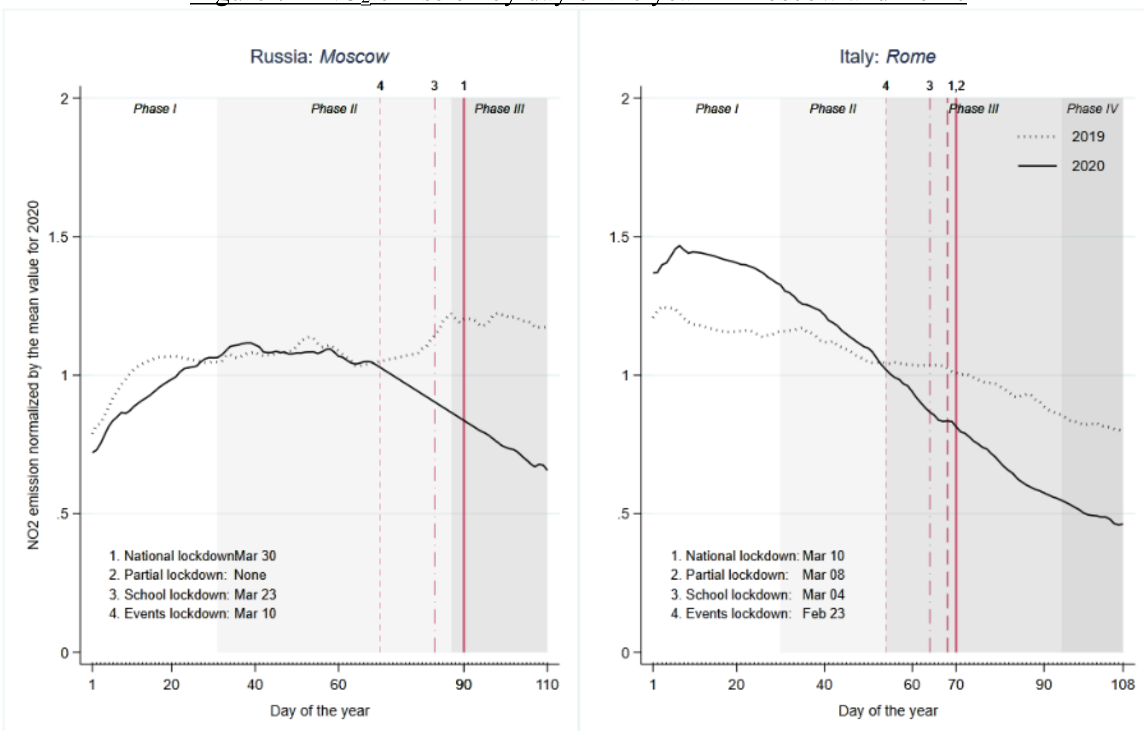


Note: These graphs plot the 30-day running mean NO_2 density (tropospheric column) for Sweden (left panel) and Bulgaria (right panel) between January 1 and April 11 of the year 2019 (dotted line) and year 2020 (solid line). Values are normalized for each country by NO_2 density on January 1th, 2020. Phase I identifies the period with no detected cases of COVID-19; Phase II starts from the day when the first case is reported; Phase III begins at the date of the first death from the disease; Phase IV identifies the period after the peak of daily deaths in the country has been reached.

Figure 6 shows the changes in the levels of NO_2 for Sweden and Bulgaria. The NO_2 levels in Sweden were declining from January to April 2020, but these levels were still higher than the levels in the corresponding days of 2019. The NPIs appear to reduce NO_2 emission in Bulgaria, where the decline started in February and continued through April of 2020. Table 4 shows the average weekly NO_2 levels by the phases of the pandemic for countries of Europe and Central Asia. Most countries show significant drops in 2020 when compared to 2019.

The NO_2 emissions are concentrated in industrial centers and large cities. The national levels of NO_2 averaged over the large territories might provide a distorted picture of the impact of the NPIs on industrial activities. Figure 7 shows the changes in levels of NO_2 for Moscow and Rome in 2020. The trends in NO_2 emissions for large cities are similar to those observed for electricity consumption and mobility. The NPIs have strong negative effects on the NO_2 emissions in both cities where declines in emissions almost exactly coincide with the public event lockdowns. Relative to the same period in 2019, the levels of emissions dropped by about 50 percent in Moscow and by 40 percent in Rome.

Figure 7 – NO_2 emission by day of the year in Moscow and Rome



Note: These graphs plot the 30-day running mean NO_2 density at the ground level in Moscow, Russia (left panel) and Rome, Italy (right panel) between January 1 and April 18 of year 2019 (dotted line) and year 2020 (solid line). Values are normalized for each city by NO_2 density on January 1^{th}, 2020. Phase I identifies the period with no detected cases of COVID-19; Phase II starts from the day when the first case is reported; Phase III begins at the date of the first death from the disease; Phase IV identifies the period after the peak of daily deaths in the country has been reached.

Table 4 – Changes in NO_2 emissions by phases of local COVID-19 outbreak

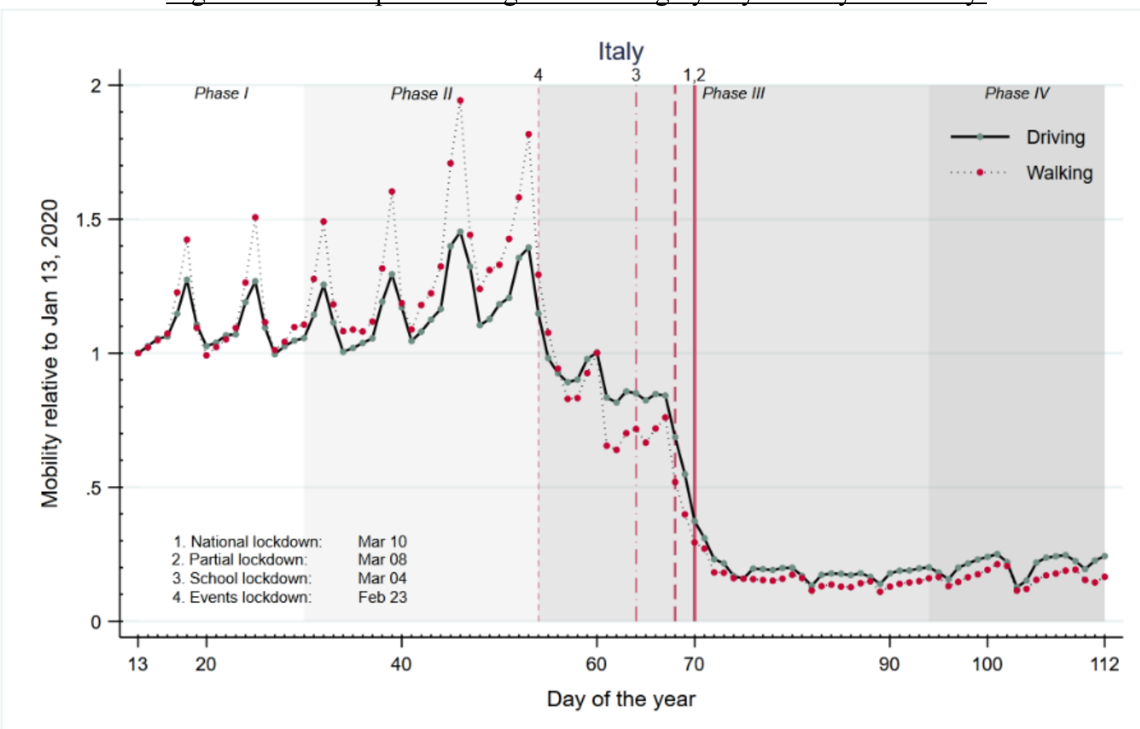
Country	2019			2020		
	Week of Phase II	*Week of Phase III*	*Week of Phase IV*	*Phase II*	*Phase III*	*Phase IV*
Albania	0.64	1.15	1.32	0.65	0.75	1.38
Armenia	0.64	0.68	.	1.08	1.06	.
Austria	0.90	0.44	.	0.51	0.48	.
Azerbaijan	0.77	0.80	.	1.15	0.91	.
Belarus	1.65	0.65	.	1.09	0.60	.
Belgium	1.34	1.00	.	.	0.95	.
B&H	0.49	0.88	1.51	0.78	0.90	1.17
Bulgaria	0.88	1.18	1.53	1.16	0.79	0.94
Croatia	0.80	1.03	.	1.13	0.98	.
Cyprus	1.30	0.74	1.36	0.96	0.58	0.80
Czech Republic	1.30	0.90	.	1.04	0.78	.
Denmark	1.65	2.00	1.02	1.13	1.05	0.64
Estonia	0.57	1.20	0.78	1.58	0.80	0.68
Finland	1.16	0.42	.	0.91	0.71	.
France	1.02	1.24	1.96	1.41	0.84	1.01
Georgia	0.41	1.18	2.41	1.01	0.49	1.04
Germany	0.95	1.05	.	1.38	1.18	.
Greece	1.14	1.09	1.21	0.91	0.87	0.99
Hungary	0.74	1.13	.	0.86	0.68	.
Iceland	0.78	0.71	0.84	0.89	0.94	1.08
Ireland	1.01	1.27	.	1.02	1.34	.
Italy	1.10	0.96	0.65	0.99	0.86	0.81
Kazakhstan	1.13	1.38	.	1.00	1.16	.
Kyrgyz Republic	1.17	1.43	1.43	1.52	1.34	1.34
Latvia	1.65	0.98	.	1.35	0.77	.
Lithuania	1.34	0.80	.	1.82	0.74	.
Malta	0.95	1.39	.	0.63	0.51	.
Moldova	0.94	0.73	0.69	0.93	0.72	0.61
Montenegro	1.34	1.75	.	1.17	1.75	.
Netherlands	2.47	0.48	1.10	0.82	1.64	1.07
North Macedonia	0.58	0.79	1.61	1.60	0.89	0.66
Norway	0.78	0.73	.	0.85	0.75	.
Poland	1.13	0.69	.	1.52	0.81	.
Portugal	0.82	1.85	.	1.01	0.86	.
Romania	0.74	0.85	.	1.45	0.74	.
Russian Federation	1.19	0.71	.	1.10	0.77	.
Serbia	1.01	1.11	0.98	1.15	0.96	0.83
Slovak Republic	0.69	0.63	.	1.01	0.53	.
Slovenia	0.92	0.73	.	1.03	0.61	.
Spain	1.01	1.16	1.11	0.96	0.96	0.93
Sweden	0.46	0.35	.	0.96	0.70	.
Switzerland	0.65	0.41	0.59	0.92	0.29	0.73
Turkey	0.88	1.31	.	1.43	1.10	.
Ukraine	1.08	1.02	.	1.15	1.17	.
United Kingdom	0.83	1.03	.	0.96	0.90	.
Uzbekistan	1.12	1.16	1.16	0.95	1.05	1.05

Note: This table indicates the average value of the 30-day running mean NO_2 density (tropospheric column) of each country for the week of the year when the first case of COVID-19 infection was reported in 2020 (phase II), for the week when the first death by COVID-19 was reported in 2020 (phase III), and for the week when the peak of daily deaths was reached in 2020 (phase IV). Empty cells indicate that the peak of daily deaths for that country had not been reached as of April 18, 2020. The values are normalized for each country by NO_2 density on January 1, 2020

5.3 Mobility

The lockdowns and other social distancing measures have a direct impact on the personal mobility and operation of many businesses. The lockdowns restrict people's movements, in many cases, to 100 meters from the building a person lives in, allowing for a limited number of trips to grocery shops and pharmacies. Closure of most businesses and switch to home-based work dramatically reduce commutes to work. Real-time data collected from mobile devices give a precise picture of the extent of the social distancing measures and the effectiveness of their enforcement.

Figure 8 – Time spent driving and walking by day of the year in Italy.



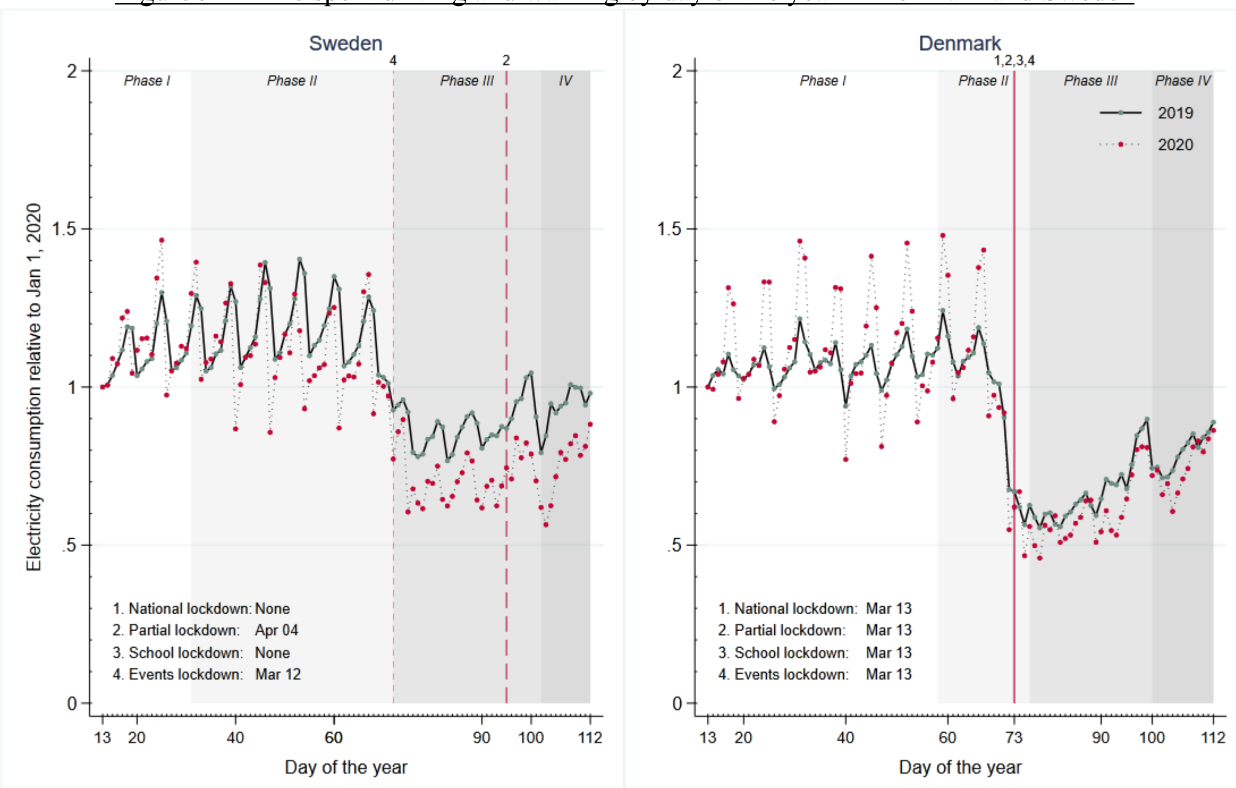
Note: Values are normalized by time driving and walking on January 13th, 2020. Phase I identifies the period with no detected cases of COVID-19; Phase II starts from the day when the first case is reported; Phase III begins at the date of the first death from the disease; Phase IV identifies the period after the peak of deaths in the country has been reached.

Figure 8 shows trends in the amount of time spent driving and walking by the day of the year in Italy. The vertical lines on the graph show the four types of NPIs. The saw-like patterns of lines on the graph reflect changes in driving and walking over the days of the week. In phase I, personal mobility increases from Monday to Friday and declines over the weekend.

The graph demonstrates a rather sharp decline in driving and walking when public events were banned in Italy on February 23. Subsequent school closings on March 4, the partial lockdown of the Lombardy region on March 8, and the national lockdown on March 10 reduced personal movements by almost 80 percent compared to the pre-pandemic period. Very pronounced weekly mobility patterns almost disappeared after the lockdowns. It appears that the social distancing measures were accepted by the majority of the Italian population and also that these measures were effectively enforced.[12] Similar mobility dynamics are observed in France, Spain, Germany, Great Britain, and other countries in Western and South Europe.

Figure 9 presents mobility patterns for Sweden and Denmark. Sweden is among the few countries in Europe that implemented no strict NPIs. Sweden did implement a ban on public events on March 12 and a partial lockdown on some activities on April 4. Denmark, instead, implemented a full lockdown on March 13.

Figure 9 – Time spent driving and walking by day of the year in Denmark and Sweden



Note: Values are normalized by time driving and walking on January 13, 2020. Phase I identifies the period with no infections detected; Phase 2 starts from the day when the first infection is registered; Phase 3 begins at the date of the first death from COVID-19; Phase IV identifies the period after the peak of deaths in the country has been reached.

Both countries experienced a decline in mobility as the local outbreak evolved. Compared to the pre-pandemic time, the time spent driving and walking declined by about 20 percent in Sweden and by about 35 percent in Denmark. These declines were much lower compared to the drop in mobility in Italy. The

[12] Civic capital appears to have played a role in the enforcement of social distancing measures. See the article by Durante, Guiso and Gulino (2020) in https://voxeu.org/article/civic-capital-and-social-distancing.

social distancing policies were apparently less strict in Denmark, and the Government of Denmark decided to ease some of the restrictions in mid-April – reflected by the strong upward trends in the level of personal mobility.

Table 5 shows the average changes in personal movement for countries in Europe and Central Asia in the first quarter of 2020. The COVID-19 pandemic and the social distancing measures implemented by the governments to limit the spread of the disease resulted in a significant reduction in driving and walking in virtually all countries in the region. By the time the countries reached a peak of daily deaths, the overall mobility had dropped by about 75% in Albania, France, Hungary, Greece, Serbia, and Spain. A significant reduction in driving and walking was also registered in Austria, Bulgaria, Poland, and Slovenia.

Table 5 – Changes in mobility patterns by phases of local COVID-19 outbreak

Country	**Driving**			**Walking**		
	Phase II	*Phase III*	*Phase IV*	*Phase II*	*Phase III*	*Phase IV*
Albania	0.94	0.32	0.24	0.88	0.37	0.26
Austria	1.15	0.65	0.44	1.18	0.57	0.39
Belgium	1.14	0.73	.	1.36	0.80	.
Bulgaria	1.00	0.60	0.38	1.07	0.61	0.38
Croatia	0.98	0.23	.	1.04	0.22	.
Czech Republic	1.15	0.44	.	1.34	0.23	.
Denmark	1.12	0.66	0.76	1.16	0.61	0.70
Estonia	1.17	0.61	0.73	1.49	0.52	0.58
Finland	1.09	0.72	.	1.00	0.61	.
France	0.98	1.06	0.25	0.92	0.99	0.16
Germany	1.05	1.06	.	1.07	1.06	.
Greece	1.15	0.56	0.24	1.14	0.58	0.23
Hungary	1.12	0.80	.	1.30	0.80	.
Iceland	1.43	0.53	0.54	1.12	0.33	0.33
Ireland	1.26	0.79	.	1.46	0.85	.
Italy	1.09	1.17	0.19	1.19	1.35	0.15
Latvia	1.12	0.64	0.64	1.27	0.49	0.45
Lithuania	1.04	0.50	0.49	1.15	0.44	0.43
Netherlands	1.01	1.02	0.53	1.19	1.18	0.56
Norway	1.11	0.66	.	1.08	0.59	.
Poland	1.02	0.60	0.34	1.14	0.53	0.23
Portugal	1.23	0.24	.	1.44	0.14	.
Romania	0.94	0.38	.	1.14	0.29	.
Russian Federation	1.07	0.78	.	1.06	0.67	.
Serbia	0.96	0.31	0.27	1.01	0.27	0.25
Slovak Republic	0.97	0.61	.	1.10	0.57	.
Slovenia	0.98	0.33	0.33	1.12	0.40	0.51
Spain	1.18	1.20	0.15	1.26	1.32	0.09
Sweden	1.15	0.91	0.93	1.16	0.77	0.69
Switzerland	1.06	1.03	0.62	1.06	1.00	0.65
Turkey	1.04	0.53	.	0.89	0.36	.
Ukraine	1.12	0.69	.	1.12	0.54	.

United Kingdom	1.06	1.08	.	1.26	1.22	.

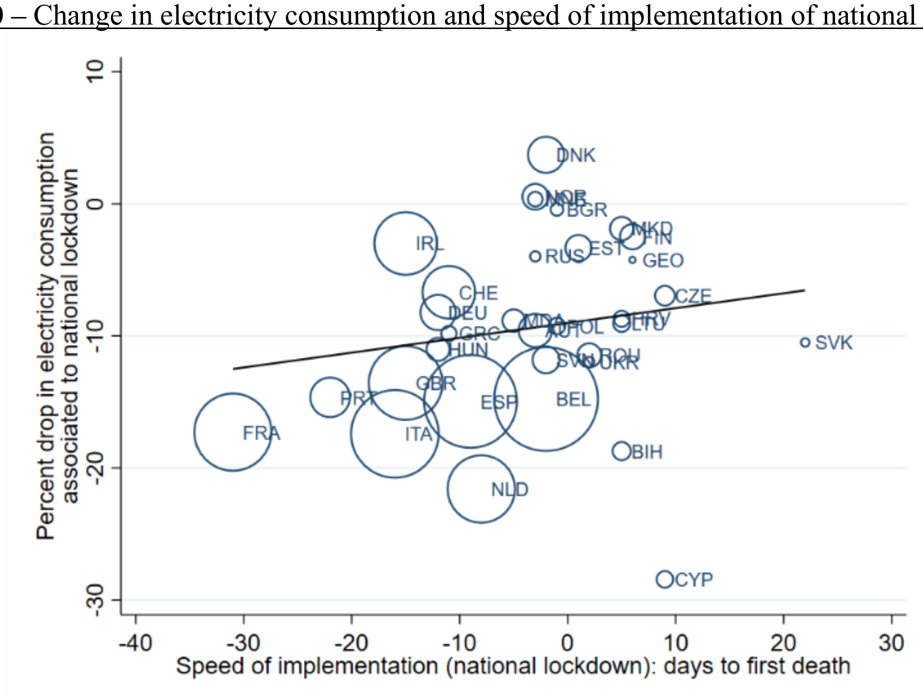
Note: this table indicates the average value of the mobility index for driving (first three columns) and walking (last three columns) for the week of the year when the first case of COVID-19 infection was reported (phase II), for the week when the first death by COVID-19 was reported (phase III), and for the week when the peak of daily deaths was reached in (phase IV). Empty cells indicate that the peak of daily deaths for that country had not been reached as of April 21, 2020. The values are normalized for each country by the electricity consumption registered on January 13, 2020.

5.4 Illustrating the early economic impact of NPIs

In this section, we investigate the association between NPIs and measures of economic activity and mobility. We first take a cursory look at the nature of the relationship. We then proceed to estimate the magnitudes using daily data and regressions.

Figure 10 plots the change in electricity consumption associated with a full, national lockdown against the speed of implementation of the full lockdown. The size of the bubbles corresponds to the mortality rate per million inhabitants as of April 25, 2020. The figure indicates that countries that implemented a lockdown earlier on in the pandemic have seen lower overall drops in electricity consumption As also hinted at in Table 2, earlier introduction of NPIs has so far resulted in lower mortality rates, and therefore the combined human and economic costs seem to have been lower for those countries that acted faster.

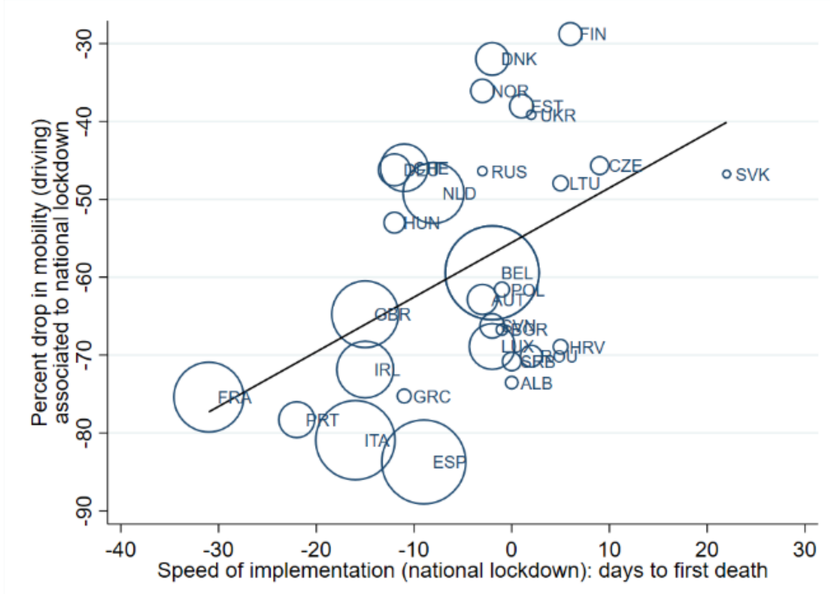
Figure 10 – Change in electricity consumption and speed of implementation of national lockdown



Note: this figure plots the relationship between the change in electricity consumption associated with a full, national lockdown (vertical axis) and the speed of implementation of the full lockdown (horizontal axis). The first variable is estimated from a country-specific regression of daily electricity consumption (covering the period 2017-2020) on a series of days of the week, week of the year, holidays and temperature dummies, and a dummy variable indicating the implementation of a national lockdown following Cicala (2020). The coefficient of the national lockdown dummy variable is plotted on the vertical axis. The speed of implementation of the full lockdown is calculated as the number of days to the first reported death by COVID-19 from the implementation date (i.e., Date of first death – Date of the lockdown). A negative value indicates that the full lockdown was implemented after the first death was reported; a positive value indicates that the lockdown was implemented before the first death was reported. The black line plots the linear fit between the change in electricity consumption and the speed of implementation. The size of the bubbles is proportional to the mortality rate per million inhabitants as of April 25, 2020.

This finding is partially explained by the fact that countries that acted faster in introducing lockdowns were able to control the pandemic despite introducing less strict lockdowns. Using mobility as a proxy for the enforcement or effective strictness of the lockdown, figure 11 shows that the speed of implementation is positively correlated with mobility: the reduction in citizens' mobility in response to the national lockdown is lower the earlier the lockdowns are imposed.[13]

Figure 11 – Change in mobility (driving) and speed of implementation of national lockdown



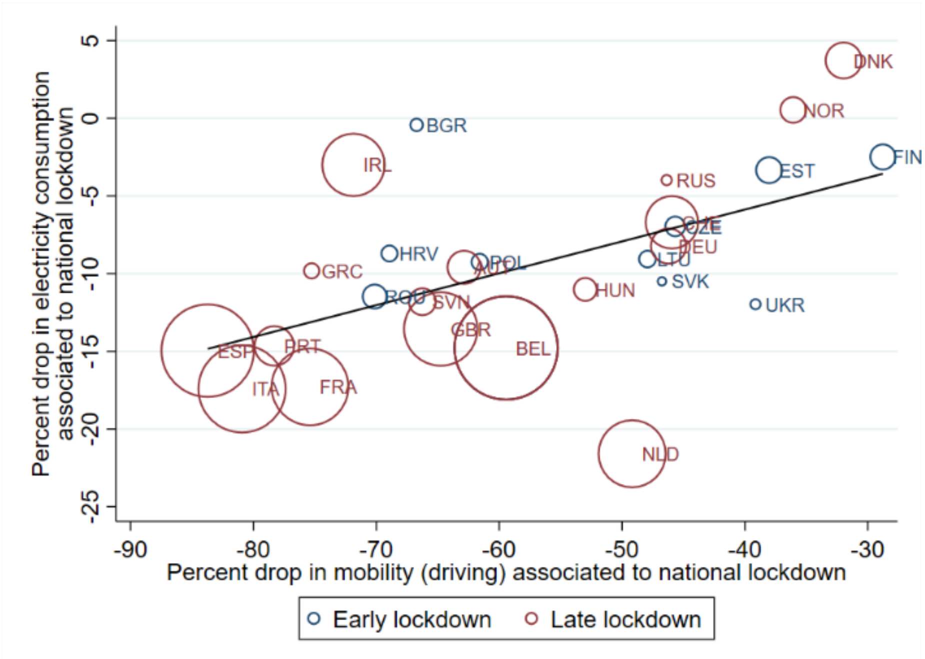
Note: this figure plots the relationship between the change in mobility (driving) associated with full, national lockdown (vertical axis), and the speed of implementation of the full lockdown (horizontal axis). The first variable is estimated as the difference in the mean mobility index for driving during the implementation of the national lockdown and the mean mobility index for driving during the pre-pandemic period (phase I: from January 13, 2020, to the day the first case was reported). The speed of implementation of the full lockdown is calculated as the number of days to the first reported death by COVID-19 from the implementation date (i.e., Date of first death – Date of the lockdown). A negative value indicates that the full lockdown was implemented after the first death was reported, a positive value indicates that the lockdown was implemented before the first death was reported. The black line plots the linear fit

[13] When using a measure of *de jure* stringency like the stringency index of government response (like the one developed by Hale et al., (2020)) the negative relationship with mobility is also present (Figure A.1). When comparing *de facto* and *de jure* stringency (Figure A.2), it emerges that countries with high mortality rates show an excess drop in mobility with respect to what *de jure* stringency would linearly predict, while countries with low mortality rates show the opposite pattern. This suggests that the mortality-driven reduction in mobility partly explains the correlation observed in figure 10: countries that implement a lockdown later do so at a time when the pandemic has spread enough to already discourage the mobility of citizens, therefore compounding the effect.

between the change in mobility and the speed of implementation. The size of the bubbles is proportional to the mortality rate per million inhabitants as of April 25, 2020.

Figure 12 puts the speed of implementation of lockdowns, their strictness, the impact on economic activity and human costs together. Plotting the change in electricity consumption associated with a full lockdown against the effective strictness of the lockdown as proxied by mobility and distinguishing between early and late lockdowns shows that late lockdowns are generally associated with greater drops in mobility - hence they tend to be more strict - and greater drops in electricity consumption. As before, the mortality rates captured by the size of the bubbles also tend to be larger for later lockdowns. In this sense, this cursory analysis suggests that faster implementation of lockdowns tends to be less stringent and, therefore, less damaging to the overall economy, while still saving human lives. In the next section, we carry out a more formal empirical analysis of these correlations.

Figure 12 – Change in electricity consumption and change in mobility (driving)



Note: this figure plots the relationship between the change in electricity associated with full lockdown (vertical axis) and the change in mobility (driving) associated with the full lockdown (horizontal axis). The first variable is estimated from a country-specific regression of daily electricity consumption (covering the period 2017-2020) on a series of days of the week, week of the year, holidays and temperature dummies, and a dummy variable indicating the implementation of a national lockdown following Cicala (2020). The coefficient of the lockdown dummy variable is plotted on the vertical axis. The variable on the horizontal axis is estimated as the difference in the mean mobility index for driving during the implementation of the national lockdown and the mean mobility index for driving during the pre-pandemic period (phase I: from January 13, 2020, to the day the first case was reported). The color of the bubble distinguishes countries in two groups: those that implemented a national lockdown early on in the pandemic (at least 1.5 days before the first reported death by COVID-19; the median speed of implementation) and those that implemented it later on (Less than 1.5 days before the first reported death by COVID-19). The black line plots the linear fit between the change in electricity consumption and the change in mobility. The size of the bubbles is proportional to the mortality rate per million inhabitants as of April 25, 2020.

6. Estimating the early economic impact of NPIs

In this section, our baseline model relates the demand for electricity in a country, as a proxy of economic activity, to the implementation of NPIs, the stage of the pandemic, and a range of controls. Our model accounts for seasonality and weekly patterns in electricity consumption, as well as the changes in electricity demand during the national holidays. We also control for differences in electricity consumption related to heating and cooling degrees.[14] The basic specification we estimate is:

$$Ln(Y_{i,t}) = \beta NPI_{i,t} + \omega H_{i,t} + \theta CH_{i,t} + \pi D_t + \gamma W_t + v_i + \epsilon_{i,t} \ , \ (1)$$

where $Y_{c,t}$ is the electricity consumption in country i on date t, $NPI_{i,t}$ is a vector of four dummies representing four types of NPIs, $H_{i,t}$ is equal to one if date t is a national holiday, $CH_{i,t}$ represents two variables for the heating and cooling days, D_t are six dummies for days of the week, W_t are week of the year dummies, v_i is the country-specific fixed effects, and $\epsilon_{i,t}$ is an i.i.d. innovation term. $\beta, \omega, \theta, \pi, and\ \gamma$ are the estimated parameters. In alternative specifications, we replace the electricity consumption by the level of NO_2 emissions in the country, as another proxy activity measure. The NPI dummies are created in such a way that each dummy indicates a period when each particular NPI was the most stringent in place. From less to more stringent, the NPIs are a ban of public events, school closure, a partial or targeted lockdown, and lastly, a full, national lockdown. For example, Germany imposed a ban on public events on March 10, school closure on March 16, and a national lockdown on March 22. For Germany, the dummy for the public event ban will have a value of one for the period from March 10 until March 16 and zero afterward; the school closure dummy switches on during the period from March 16 until March 22, and the national lockdown dummy activates on March 22.

In specification (1), the coefficients β could be interpreted as estimates of the effects of the government-mandated NPIs on both aggregate demand and supply.[15] The social distancing measures reduce aggregate supply by forcing workers to stay home and decrease aggregate demand by negatively affecting the consumption of services, particularly those that involve direct contact with customers or clients. The pandemic directly affects labor supply by reducing the number of workers because of sickness and lowering

---

[14] To approximate the heating demand, we use the number of hours during the day when the ambient temperature was below 18 C (65 F); cooling demand is approximated by the number of hours in a day when the ambient temperature exceeded 24 C (75 F).

[15] Note that this specification treats school closures in the same way independently of whether a ban of public events was in place or not, and it treats a partial or targeted lockdown in the same way independently of whether a ban of public events or a school closure was in place or not. The partial correlations captured by β for the ban of public events, school closure and partial lockdown therefore correspond to the average way in which these NPIs were implemented in the sample. This is not the case for the partial correlation corresponding to the full, national lockdown, the most stringent NPI, which necessarily includes a ban of public events, school closure and any kind of partial or targeted lockdown.

the productivity of sick workers. The fears and uncertainties associated with the progression of the pandemic resulted in a sharp increase in grocery spending and in a dramatic drop in expenditures on restaurants, retail, travel, and public transportation that translates into reduced energy demand (Baker at al., 2020). To estimate these effects, we expand specification (1) by adding health measures of pandemic progression. The new specification then becomes:

$$Ln(Y_{i,t}) = \beta NPI_{i,t} + \vartheta P_{i,t} + \omega H_{i,t} + \theta CH_{i,t} + \pi D_t + \gamma W_t + v_i + \epsilon_{i,t} \ , \quad (2)$$

where $P_{i,t}$ is the daily number of deaths per million due to COVID-19.[16]

Any measure of pandemic progression is endogenous in specification (2) since some unobserved factors could affect both the demand for electricity and the human impact of the pandemic. To address these concerns, we instrument the death rate in (2) with the daily predictions from a standard SIR epidemiological model that assumes an unmitigated spread of the disease (no NPIs implemented), and where the cross-country variation comes only from pre-pandemic characteristics like the demographic profile of the country, the number of ICU beds and an initial rate of contagion.[17]

Table 6 provides the fixed effect regression estimations of electricity consumption and NO_2 emissions, for specifications (1) and (2). The last two pairs of columns present the IV estimations for both dependent variables.

[16] Using the daily number of infected individuals per million does not change the main results.
[17] The model was initially developed by a team at the University of Basel. The online tool providing the country-specific scenarios is available in https://covid19-scenarios.org/.

Table 6: Fixed effect and Instrumental Variable Fixed effect regression results of the response of electricity consumption and NO_2 emission levels to the COVID-19 pandemic and NPIs.

Note: this table reports estimates from the following panel regression model:

$$Ln\left(Y_{i,t}\right) = \alpha + \beta_{NL}NL_{i,t} + \beta_{PL}PL_{i,t} + \beta_{SC}SC_{i,t} + \beta_{BP}BP_{i,t} + \vartheta P_{i,t} + \omega H_{i,t} + \theta_C Cool_{i,t} + \theta_H Heat_{i,t} + \pi D_t + \gamma W_t + Year_t + v_i + \epsilon_{i,t}$$

Where $Y_{i,t}$ is either daily electricity consumption (columns 1, 2, and 5) or daily 30-day running mean of NO_2 emissions (columns 3, 4 and 6) for country *i* on date *t*. *NL, PL, SC,* and *BP* are dummy variables that take a value of one if a national lockdown (*NL*), a partial lockdown (*PL*), school closure (*SC*) or a ban of public events (*BP*) were in place in country *i* on date *t*. *BP* takes a value of zero if either *SC*, *PL* or *NL* take a value of one. *SC* takes a value of zero if either *PL* or *NL* take a value of one. *PL* takes a value of zero if *NL* takes a value of one. $P_{i,t}$ is the 7-day moving average of daily deaths by COVID-19, expressed per million people. *H* is a dummy for the national holidays; *Cool* is a variable indicating the number of hours in day *t* where the average ambient temperature in country *i* was higher than 24Cº/75Fº. *Heat* is a variable indicating the number of hours in day *t* where the average ambient temperature in country *i* was lower than 18Cº/64Fº. *D* and *W* are the day of the week and week of the year dummies respectively; *Year* is a year dummy, and *v* is the country fixed effect. The coefficients for *H*, *Cool*, *Heat*, *D*, *W*, *Year,* and *v* are omitted from the table. Columns 1 to 4 estimate the panel model with ordinary least squares with fixed effects. In columns 5 and 6, $P_{i,t}$ is instrumented with the daily deaths by COVID-19 estimated by a SIR epidemiological model that assumes unmitigated spread of the disease (no NPIs in place). The coefficient on the instrument in the first stage regression are also shown in columns 5 and 6. We report the first stage F-statistic and the weak ID test, which is the Stock-Yogo weak identification test with critical values: 10% maximal IV size=16.38 15%=8.96 20%=6.66 25%=5.9363. *** indicates that the coefficient is significant at 1% level, ** - at 5% level, * - at 10% level

	Log of Electricity consumption				Log of NO_2 emission level				Log of Electricity consumption		Log of NO_2 emission level	
	OLS				OLS				IV		IV	
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coef.	*S. Err.*	Coef.	*S. Err.*	Coef.	*S. Err.*	Coef.	*S. Err.*	Coef.	*S. Err.*	Coef.	*S. Err.*
Non-pharmaceutical interventions (NPI)												
National lockdown	-0.119***	*0.014*	-0.111***	*0.015*	-0.187***	*0.034*	-0.174***	*0.036*	-0.077***	*0.023*	-0.196***	*0.036*
Partial lockdown	0.042	*0.026*	-0.016	*0.027*	-0.118**	*0.057*	-0.114**	*0.057*	-0.011	*0.030*	-0.145**	*0.060*
School closure	-0.023	*0.026*	0.043	*0.026*	-0.114**	*0.054*	-0.112**	*0.054*	0.047*	*0.026*	-0.060	*0.052*
Ban on public events	-0.105**	*0.036*	-0.104**	*0.036*	-0.244***	*0.063*	-0.243***	*0.063*	-0.103**	*0.036*	-0.313***	*0.059*
Pandemic progression indicators												
Daily deaths per million			-0.005*	*0.003*			-0.008	*0.007*	-0.023***	*0.003*	-0.004	*0.008*
First Stage Instruments												
Modeled death rate									0.312***	*0.001*	0.324***	*0.002*
F-test									514.30		210.46	
Weak identification test									3,800		1,300	
# of observations	38,399		38,399		8,487		8,487		38,399		8,487	
# of countries	33		33		33		33		33		33	

The results of the fixed effect regression of specification (1) without controls for the progression of the pandemic shown in the first column of Table 6 demonstrate that, on average, for 33 European countries, the national lockdown leads to about 12 percent reduction in electricity consumption. The ban on public events produces a similar effect. Partial lockdowns and school closures have no significant impact on electricity consumption, most likely because, in many countries, the dates of implementation of the measures were close to when the national lockdown was imposed.[18]

The second column of Table 6 shows the estimation of the specification with an added variable on the progression of the pandemic. The addition of the daily deaths per million inhabitants does not affect the NPI coefficients significantly.[19] An extra death per million inhabitants reduces electricity consumption by about 0.5 percent. The average peak of daily deaths in the sample is 4.2 deaths per million inhabitants, suggesting that the average country may have seen a decrease of more than 2 percent in electricity consumption associated with the pandemic at the local outbreak's peak.

The fifth column of Table 6 shows the results of the fixed effect regression, where the progression of the pandemic is instrumented by the model predictions.[20] Accounting for the endogeneity of the death rates attenuates the effect of NPIs and increases the effect of this variable on electricity consumption. Using these estimates, at the peak of the pandemic, the average country in the sample may have seen a decrease of 9.7 percent in electricity consumption. This effect is higher than the average 7.7 percent decrease in electricity consumption due to the full lockdown in the same specification, illustrating how both NPIs and the spread of the disease itself can be equally relevant in explaining the decrease in electricity consumption during the pandemic's worst days.

In order to assess the economic magnitude of the NPIs' impact, it is necessary to assign a value to the elasticity between the proxy measures of economic activity and actual economic indicators. The elasticity that is required for this analysis emerges from the short-term correlation between both variables – it does not relate to long-term trends, which could be affected by technological changes.

---

[18] Results are similar if each NPI dummy is included on its own in different specifications. The coefficients associated with the national lockdown, the ban of public events and school closure are separately negative and statistically significant. The coefficient for the partial lockdown is positive, but this is probably due to the fact that national lockdowns (which have a larger negative effect) were in place in the majority of the country sample at the same time as partial lockdowns were in place in a subset of countries.

[19] We also estimate the regressions where we use daily infection rates as an indicator for the pandemic's progression. These estimations produce similar results in terms of the impact of the NPIs on both electricity and NO_2 emissions. The effects of the daily infection rates on the economic activity indicators are not significant.

[20] The Stock-Yogo weak identification test using the Craig-Donald F statistic is highly significant as is the standard F-test of the first stage.

The elasticity between electricity consumption and short-term, standard economic indicators has been established to be close to 1 (Cicala, 2020). So, the above estimates represent short-term economic impact. However, NO_2 emissions have a smaller elasticity with respect to short-term economic activity. Appendix 3 presents a simple calculation of the elasticity between NO_2 emissions in China and short-term economic indicators of the country during January-February 2020, when the country implemented several NPIs to contain the local COVID-19 outbreak. The estimates of elasticity vary from 0.32 to 1 depending on the chosen economic indicator. Table 7 provides a summary of the elasticities of the different proxy measures.

Table 7 – Elasticities of proxy measures of activity and economic indicators

Proxy measure (country level)	Economic indicator (country level)	Elasticity
Daily electricity consumption	Economic activity (Cicala, 2020)	~1.00
	Value added in industrial enterprises	0.32
Monthly NO_2 emissions	Index of services production	0.33
	Retail sales of consumer goods	0.50
Weekly NO_2 emissions	FT China economic activity index	1.00

Note: this table indicates the elasticities (rightmost column) of different proxy measures of economic activity (leftmost column). The center column indicates the economic indicator for which these elasticities are calculated. See Appendix 2 for more details on the elasticities calculated for NO_2 emissions variables.

When we use NO_2 emissions as an alternative dependent variable in Table 6, we are able to extend the sample to include 48 countries in Europe and Central Asia. Since NO_2 emissions tend to be noisy, we use a 30-day running mean to smooth the data. However, NO_2 levels are also less dependent on the behavioral response of the population to the progression of the pandemic, since they depend to a larger degree on industrial activity and transport. The results of the estimations using electricity consumption are confirmed by similar results when using NO_2 emissions. Table 8 demonstrates that NPIs have a strong negative impact on the levels of NO_2 emissions.[21] Using the mid-point elasticities of GDP with respect to NO_2 emissions calculated for China (0.66), the -17% decrease in the levels of NO_2 associated with a national lockdown would be equivalent to about a -11% decrease in aggregate output. This decline is similar to the estimates derived from the regressions on electricity consumption (where that elasticity is close to 1).

[21] Unreported regressions (available upon request) show that NPIs are also associated with a significant decrease of NO_2 measurements at the city-level. The city readings are obtained from the ground stations and may not be representative of a country's total emissions, while the national data are obtained from satellite readings. Hence, the two are not comparable.

Table 8: Fixed effect regression results of the response of electricity consumption to the speed and stringency of NPIs.

This table reports estimates from the following panel regression model:

$$Ln(Y_{i,t}) = \alpha + \beta_{NL}NL_{i,t} + \beta_{NLD}NL_{i,t} \times Speed_i + \beta_{NLS}NL_{i,t} \times Stringency_i + \beta_{NLM}NL_{i,t} \times Mobility\_drop_i + \beta_{PL}PL_{i,t} + \beta_{SC}SC_{i,t} + \beta_{BP}BP_{i,t} + \vartheta P_{i,t} + \omega H_{i,t} + \theta_C Cool_{i,t} + \theta_H Heat_{i,t} + \pi D_t + \gamma W_t + Year_t + v_i + \epsilon_{i,t}$$

Where $Y_{i,t}$ is the daily electricity consumption for country i on date t. NL, PL, SC and BP are dummy variables that take a value of one if a national lockdown (NL), a partial lockdown (PL), school closure (SC) or a ban of public events (BP) were in place in country i on date t. BP takes a value of zero if either SC, PL or NL take a value of one. SC takes a value of zero if either PL or NL takes a value of one. PL takes a value of zero if NL takes a value of one. *Speed* indicates the number of days elapsed from the implementation of the national lockdown to the day when the first death by COVID-19 was reported in the country. A negative number indicates that the lockdown was implemented late, after the first death was reported. *Stringency* indicates the mean value of the stringency index of government response during the period when the national lockdown was in place. The index ranges from 0 (least stringent) to 100 (most stringent). *Mobility_drop* indicates the drop in mobility associated to the national lockdown measured as the difference in average mobility (driving) during the lockdown with respect to January 13th, 2020. The coefficients θ_{NLD}, θ_{NLS}, and θ_{NLM} capture the partial correlation of the **interaction** between the national lockdown dummy NL and the *Speed*, *Stringency,* and *Mobility_drop* variables respectively. The columns 1 and 2 include only the interaction with *Speed*; columns 3 and 4 include only the interaction with *Stringency*; columns 5 and 6 include only the interaction with *Mobility_drop*. $P_{i,t}$ is the 7-day moving average of daily deaths by COVID-19, expressed per million people. H is a dummy for the national holidays; *Cool* is a variable indicating the number of hours in day t where the average ambient temperature in country i was higher than 24Cº/75Fº. *Heat* is a variable indicating the number of hours in day t where the average ambient temperature in country i was lower than 18Cº/64Fº. D and W are the day of the week and week of the year dummies respectively; *Year* is a year dummy, and v is the country fixed effect. The coefficients for H, *Cool*, *Heat*, D, W, *Year,* and v are omitted from the table. The panel model is estimated with ordinary least squares with fixed effects. The results in the last two columns of the table are most likely to be biased due to the reverse causality problem. We show these only for illustration purposes. *** indicates that the coefficient is significant at 1% level, ** - at 5% level, * - at 10% level.

	Log of Electricity consumption											
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coef.	*S. Err.*	Coef.	*S. Err.*	Coef.	*S. Err.*	Coef.	*S. Err.*	Coef.	*S. Err.*	Coef.	*S. Err.*
Speed in implementation of national lockdown	0.003**	0.001	0.002**	0.001								
Stringency of the national lockdown					-0.002***	0.000	-0.002***	0.000				
Drop in mobility									-0.114***	*0.014*	-0.085***	*0.014*
National lockdown	-0.111***	0.015	-0.107***	0.016	0.031	0.062	0.001	0.026	0.010	*0.011*	-0.007	*0.012*
Partial lockdown	-0.008	0.036	-0.000	0.036	0.024	0.041	-0.019	0.027	-0.062***	*0.011*	-0.054***	*0.010*
School closure	0.046**	0.028	0.046**	0.028	0.063*	0.036	0.043*	0.026	-0.028**	*0.009*	-0.026**	*0.009*
Ban on public events	-0.102**	0.038	-0.102**	0.038	-0.069**	0.036	-0.105**	0.036	-0.007**	*0.008*	-0.008	*0.008*
Daily deaths per million			-0.003	0.002			-0.003	0.003			-0.005***	*0.001*
# of observations	35,983		35,983		29,987		29,987		2,402		2,402	
# of countries	31		31		26		26		25		24	

Table 8 illustrates the effect of the speed of NPI implementation and the stringency of NPIs on electricity consumption. The speed of NPI implementation is defined as the number of days elapsed from the date when an NPI was implemented to the date of the first death from COVID-19. In that definition, the variable is negative (delayed or slow implementation) if an NPI was implemented after the first death was reported; the variable is positive otherwise. In the regressions, we focus on the speed of the national lockdown implementation, and thus we interact the national lockdown dummy with its corresponding speed variable. The stringency of the national lockdown is measured by two different variables. The first one represents the *de jure* stringency of the lockdown, and it consists of the average value of the government response stringency index during the period when a full lockdown was in place. The index ranges from 0 (less stringent) to 100 (most stringent) and is based on the policy decisions taken by governments on several areas: workplace restrictions, mobility restrictions, school closure, and restrictions on gatherings and public events (Hale et al., 2020). This index is available only for 26 countries in Europe and Central Asia. An alternative measure of stringency, more related to the *effective* or *de facto* stringency of the lockdown, is the average drop in mobility observed during the period when the lockdown was in place. Just as with the speed variable, in the regressions, we interact the stringency variables with the national lockdown dummy.

The first two columns in Table 8 show that countries that implemented the national lockdown earlier experienced a smaller decline in electricity consumption compared to countries that imposed national lockdowns on later stages of the pandemic. A full lockdown implemented on the day of the first death is associated with a decrease in electricity consumption of 11 percent. For each day of delay, the drop in electricity consumption due to the full lockdown is increased by 0.3 percent. Implementing the lockdown one week before the first death is associated with a reduction in the drop in electricity consumption of more than 2 percent. The average delay in the sample is about 3.3 days, suggesting the average country incurred an additional 1 percent decrease in electricity consumption due to the late implementation of the full lockdown. When the daily death rate is included in the regression (column 2), the results barely change, and the daily death rate variable itself is not statistically significant. This is not surprising given that the speed variable is capturing part of the variability of the evolution of the pandemic: as seen in Table 2, earlier introduction of NPIs leads to lower peak daily death rates. In this sense, these results suggest that speedy NPIs are economically less damaging because they limit the decline in activity associated with the spread of the disease.

Results are similar when analyzing the *de jure* stringency of NPI implementation in columns 3 and 4 of Table 8. The average stringency of the national lockdown in the sample is 80.2 (on a scale from 0 to 100), implying that the average country in this sample of 26 countries saw a decrease of 16 percent in electricity consumption associated with the full lockdown. The most stringent lockdown in the sample -with a value of 99.3 in the stringency index- is associated to a decrease of almost 20 percent in electricity consumption, while the least stringent one -with a value of 51.6 in the stringency index- is associated with a 10 percent drop in electricity consumption. Again, once *de jure* stringency is included in the analysis, the effect capturing the evolution of the pandemic -as measured by the daily deaths by COVID-19- becomes statistically not significant (column 4). This suggests that, just like for the speed of implementation, the stringency of a lockdown already captures most of the meaningful variation associated with the spread of the disease.

Columns 5 and 6 of Table 8 use the average drop in mobility associated with the lockdown as a measure of *de facto* stringency. Results have to be interpreted with caution because mobility itself may have a direct effect on electricity consumption beyond any variation induced by the lockdown itself, and there is also a possibility of reverse causality – drops in economic activity (electricity consumption) may themselves cause a drop in mobility. Therefore, the estimated coefficients may be biased. We present these results for illustration purposes: they show that a *de facto* more stringent lockdown is indeed more economically damaging.

As shown in section 5.4, speed and stringency are correlated: a simple cross-country correlation suggests that an additional week of delay in the implementation of a national lockdown is associated with a 1.4% more *de jure* stringent lockdown and a 5% more *de facto* stringent lockdown.[22] Delayed lockdowns compound the effect of the pandemic: for a given level of *de jure* stringency, *de facto* stringency is higher the slower the implementation of the lockdown,[23] which is also associated with a higher mortality rate.

7. Conclusion

The COVID-19 pandemic has caused a huge economic and human cost since its outbreak in early 2020. While there is ample theoretical work on the economic implications of the pandemic, empirical estimates of the size of the economic shocks triggered by the spread of the disease and associated NPIs have been scarce, since official economic indicators are only made available with a lag. In this paper, we provide an illustration of the early economic impact by tracking the evolution of high-frequency variables, which proxy economic activity. In particular, we show the effect of the pandemic on daily measurements of electricity consumption, NO_2 emissions, and mobility across Europe and Central Asia.

Proxy measures of economic activity allow us to investigate the economic impact of non-pharmaceutical interventions, which have been the main public health policy implemented by governments around the

[22] Partial correlations estimated from the linear fit regressions in figures A.1 and 11 respectively.

[23] The partial correlation between excess mobility drop (defined as the difference between the predicted drop in mobility for a given level of *de jure* stringency) and the speed of implementation is positive and statistically significant. See Appendix figure A.3.

world to contain the pandemic. It has been argued that these NPIs, while useful in "flattening the curve" of health costs, may come at high economic costs. Our results suggest that NPIs, specifically national lockdowns, are associated with a decline in economic activity of around 10 percent across the region, whether we measure economic activity by electricity use or emissions data. Nevertheless, our empirical analysis shows that at least until today, countries that have acted earlier in the course of the pandemic -by implementing NPIs well before the first deaths by COVID-19 were reported- have seen smaller drops in economic activity associated with a full lockdown, in part because they have been less stringent. Moreover, there is evidence that the COVID-19 mortality at the peak of the local outbreak as well as aggregate mortality have been lower for countries that acted earlier. In this sense, our results suggest that the sooner NPIs are implemented, the better the economic and health outcomes.

The analysis in this paper also shows that the spread of the disease itself has an economic impact distinct from that of NPIs: at the peak of the outbreak the drop in activity associated with the spread of the disease -be it by incapacitation of workers or by the precautionary reaction of consumers and investors- can be as strong as the shock triggered by lockdown measures. The smaller economic fallout of speedier interventions can also be explained by their effectiveness in containing the spread of the disease and, therefore, limiting the economic damage of the pandemic itself. These initial NPIs also provided a much-needed breathing space for developing testing and contact tracing capacity in many countries, which can be put to use in designing a better and faster response to the next wave of infections.

At a time when countries in the region are grappling with ways of relaxing lockdown measures, our results suggest that policy makers should be cautious in reopening their economies too fast. The drop in economic activity observed when lockdowns are in place is not solely explained by the lockdown restrictions themselves but is also associated with the behavioral response to the spread of the disease. Therefore, a fast reopening that generates a rebound in the spread of the disease can be damaging not only in human terms, but also in economic ones. An unexpected increase in the infection rates or the number of deaths after opening up might slow down or even reverse positive economic trends.

The pace of the pandemic requires new approaches to empirical analysis. We demonstrate that easily available and often free data, such as hourly electricity consumption or high-resolution satellite imagery of NO_2 concentration and, potentially, luminosity data, could be reliably used for assessing the economic effect of the pandemic almost in real-time. The applicability of such data would diminish with time when economic actors adjust their behavior to the new environment. Still, these data appear to be invaluable for short-term assessments. More effort should go into establishing and calibrating the relationships between these proxies and the actual economic output.

References

Acemoglu, D., Chernozhukov, V., Werning, I. and M.D. Whinston (2020) "A Multi-Risk SIR Model with Optimally Targeted Lockdown", NBER Working Paper No. 27102

Almond, D. (2006). "Is the 1918 Influenza Pandemic Over? Long-term Effects of In Utero Influenza Exposure in the post-1940 U.S. Population." in *Journal of Political Economy* vol. 114, n. 4: 672–712.

Almond, D. and B. Mazumder (2011) "Health Capital and the Prenatal Environment: The Effect of Ramadan Observance during Pregnancy" in *American Economic Journal: Applied Economics*, vol. 3, n.4: 56-85

Aum, S., Lee, S.Y. and Y. Shin (2020) "Inequality of Fear and Self-Quarantine: Is There a Trade-off between GDP and Public Health?", NBER Working Paper No. 27100

Baker, S., Farrokhnia, R., Meyer, S., Pagel, M., and C. Yannelis (2020) "How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic", NBER Working Paper No. 26949

Bali, S.; Baris, E.; Gatti, R.; Kitamura, A.; Secci, F. and D. Wilson (2020) "Considerations on Surge Response to Coronavirus Disease 2019 in Italy", World Bank Brief

Barro, R. J.; Ursúa, J. F. and J. Weng (2020). "The Coronavirus and the Great Influenza Pandemic: Lessons from the "Spanish Flu" for the Coronavirus's Potential Effects on Mortality and Economic Activity." NBER Working Paper 26866

Brainerd, E. and M. V. Siegler (2003). "The Economic Effects of the 1918 Influenza Epidemic." CEPR Discussion Paper 3791

Calabrese, F., Diao, M., Di Lorenzo, G., Ferreira, J. and C. Ratti (2013) "Understanding Individual Mobility Patterns from Urban Sensing Data: A Mobile Phone Trace Example" in *Transportation Research Part C: Emerging Technologies*, vol. 26: 301-313

Chang, R. and A. Velasco (2020) "Economic Policy Incentives to Preserve Lives and Livelihoods", NBER Working Paper 27020

Chen, X. and W. D. Nordhaus (2011) "Using Luminosity Data as a Proxy for Economic Statistics" in *Proceedings of the National Academy of Sciences*, vol. 108, n.21: 8589-8594

Cicala, S., (2020) "Early Economic Impacts of COVID-19 in Europe: A View from the Grid", University of Chicago, https://home.uchicago.edu/~scicala/papers/real_time_EU/real_time_EU.pdf

Correia, S.; Luck, S. and E. Verner (2020) "Pandemics Depress the Economy, Public Health Interventions Do Not: Evidence from the 1918 Flu", mimeo available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3561560

Eichenbaum, M. S.; Rebelo, S. and M. Trabandt (2020). "The Macroeconomics of Epidemics" NBER Working Paper 26882.

EuroMOMO (2020) "European mortality bulletin week 15, 2020" available at:https://www.euromomo.eu/bulletin_pdf/2020/2020_15_bulletin.pdf

EIA (2020) "EIA's Hourly Electric Grid Monitor provides timely data about electricity usage patterns", Today in Energy, April 6, 2020. https://www.eia.gov/todayinenergy/detail.php?id=43295&src=email

Fang, H., Wang, L. and Y. Yang (2020) “Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCOV) in China”, NBER Working Paper 26906

Fernald, J.; Malkin, I. and M. Spiegel (2013) “On the Reliability of Chinese Output Figures” *Federal Reserve Bank of San Francisco Economic Letter,* vol. 8: 1–5.

Garrett, T. A. (2009). “War and Pestilence as Labor Market Shocks: U.S. Manufacturing Wage Growth 1914–1919.” in *Economic Inquiry*, vol. 47, n. 4: 711–725.

Gourinchas, P.-O. (2020) “Flattening the Pandemic and Recession Curves” in Baldwin, R. and Weder di Mauro, B. (eds.) Mitigating the COVID Economic Crisis: Act Fast and Do Whatever it Takes, a VoxEU.org e-book, CEPR press.

Guerrieri, V.; Lorenzoni, G., Straub, L. and I. Werning (2020) “Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?” NBER Working Paper 26918

Guimbeau, A.; Menon, N. and A. Musacchio (2020) “The Brazilian Bombshell? The Long-Term Impact of the 1918 Influenza Pandemic the South American Way” NBER Working Paper 26929

Hale, T., Angrist, N., Kira, B., Petherick, A., Phillips, T., and S. Webster (2020) " Variation in government responses to COVID-19," Blavatnik School of Government, BSG Working Paper, BSG-WP-2020/032

Hawelka, B.; Sitko, I.; Beinat, E.; Sobolevsky, S.; Kazakopoulos, P. and C. Ratti (2014) “Geo-located Twitter as Proxy for Global Mobility Patterns” in *Cartography and Geographic Information Science*, vol. 41, n.3: 260-271

Henderson, J.V.; Storeygard, A. and D. Weil (2012) “Measuring Economic Growth from Outer Space” in *American Economic Review*, vol. 102, n.2: 994-1028

International Monetary Fund (2006) “Jamaica: Selected Issues”. IMF Country Report 06/157

Institute for Health Metrics and Evaluation (2017) “GBD Compare” Available online at http://www.healthdata.org/data-visualization/gbd-compare

Jordà, Ò. ; Singh, S.R. and Taylor, A.M. (2020) “Longer-run Economic Consequences of Pandemics” NBER Working Paper 26934

Koech, J. and J. Wang (2012) “China’s Slowdown May Be Worse than Official Data Suggest” *Federal Reserve Bank of Dallas Economic Letter* vol. 7, n. 8: 1–4.

Lewis, D.; K. Mertens and J. H. Stock (2020) “U.S. Economic Activity During the Early Weeks of the SARS-COV-2 Outbreak”, NBER Working Paper 26954

Morris, S. and J. Zhang (2019) “Validating China’s Output Data Using Satellite Observations” in *Macroeconomic Dynamics*, vol. 23: 3327-3354

Velde, F. (2020) “What Happened to the US Economy During the 1918 Influenza Pandemic? A View Through High-Frequency Data”, Working Paper 2020-11, Federal Reserve Bank of Chicago.

World Bank (2020) “Semiannual Report of the Latin America and Caribbean Region: The Economy in the Time of Covid-19”, Chief Economist Office for Latin America and the Caribbean and Macroeconomics, Trade and Investment Global Practice, World Bank: Washington, DC.

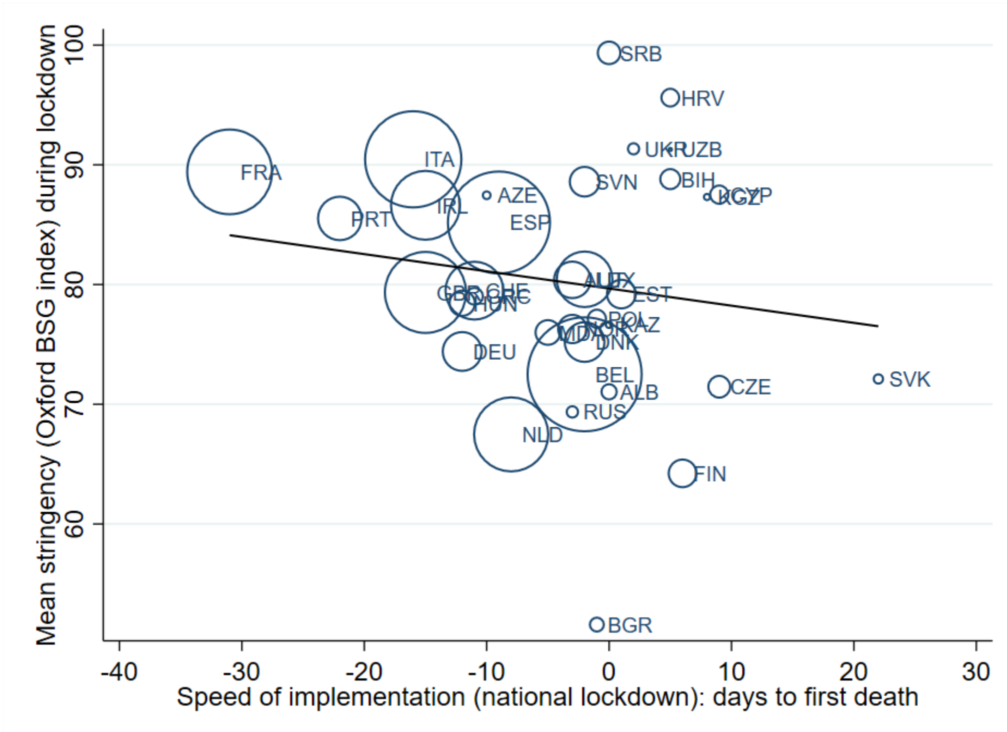
Wren-Lewis, S. (2020) "The Economic Effects of a Pandemic" in Baldwin, R. and Weder di Mauro, B. (eds.) Economics in the Time of COVID-19, a VoxEU.org e-book, CEPR press.

Appendix 1: Tables and Figures

Table A1: Data coverage for three proxies of economic activity by country.

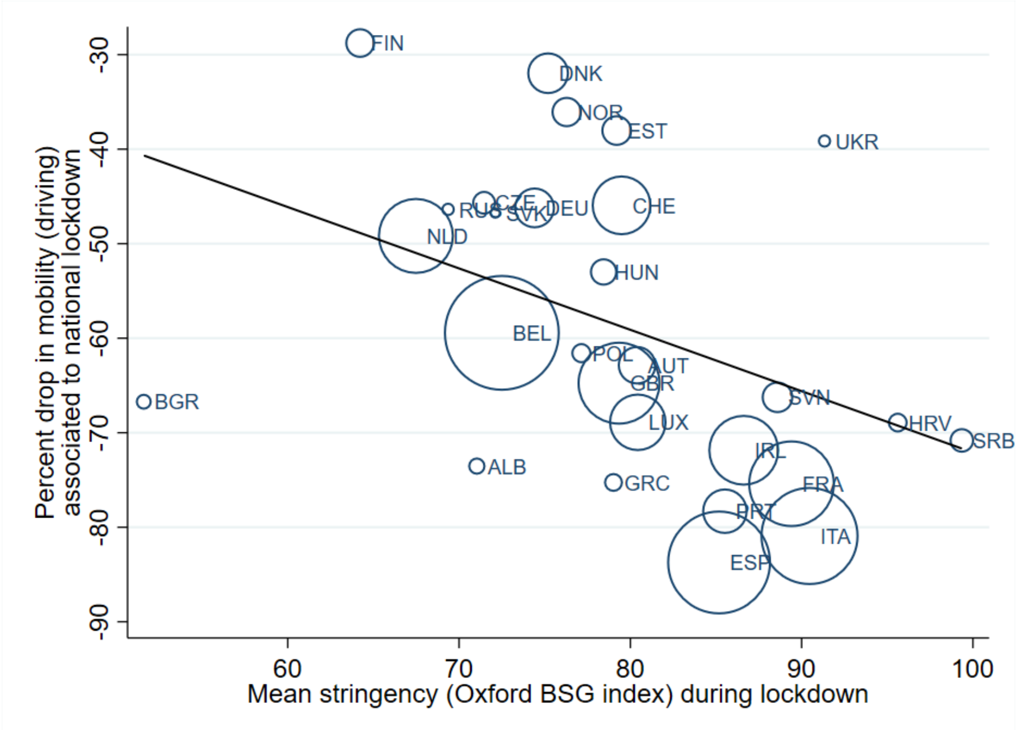
Country	Electricity	NO2 (country)	NO2 (city)	Mobility
Albania	.	✓	.	✓
Armenia	.	✓	.	.
Austria	✓	✓	✓	✓
Azerbaijan	.	✓	.	.
Belgium	✓	✓	✓	✓
Bulgaria	✓	✓	✓	✓
Bosnia and Herzegovina	✓	✓	✓	.
Belarus	.	✓	.	.
Switzerland	✓	✓	.	✓
Cyprus	✓	✓	.	.
Czech Republic	✓	✓	✓	✓
Germany	✓	✓	✓	✓
Denmark	✓	✓	✓	✓
Spain	✓	✓	✓	✓
Estonia	✓	✓	-	✓
Finland	✓	✓	✓	✓
France	✓	✓	✓	✓
Georgia	✓	✓	.	.
Greece	✓	✓	.	✓
Croatia	✓	✓	✓	✓
Hungary	✓	✓	✓	✓
Ireland	✓	✓	✓	✓
Iceland	.	✓	.	✓
Italy	✓	✓	✓	✓
Kazakhstan	.	✓	.	.
Kyrgyz Republic	.	✓	.	.
Kosovo	.	✓	.	.
Lithuania	✓	✓	.	✓
Luxembourg	.	✓	.	.
Latvia	✓	✓	.	✓
Moldova	✓	✓	.	.
North Macedonia	✓	✓	.	.
Malta	.	✓	.	.
Montenegro	✓	✓	.	.
Netherlands	✓	✓	✓	✓
Norway	✓	✓	✓	✓
Poland	✓	✓	✓	✓
Portugal	✓	✓	✓	✓
Romania	✓	✓	✓	✓
Russian Federation	✓	✓	✓	✓
Serbia	✓	✓	✓	✓
Slovak Republic	✓	✓	✓	✓
Slovenia	✓	✓	.	✓
Sweden	✓	✓	.	✓
Tajikistan	.	✓	.	.
Turkmenistan	.	✓	.	.
Turkey	✓	✓	✓	✓
Ukraine	✓	✓	.	✓
United Kingdom	✓	✓	✓	✓
Uzbekistan	.	✓	.	.

Figure A.1 – Mean stringency of government response (Oxford BSG index) during full lockdown and speed of implementation



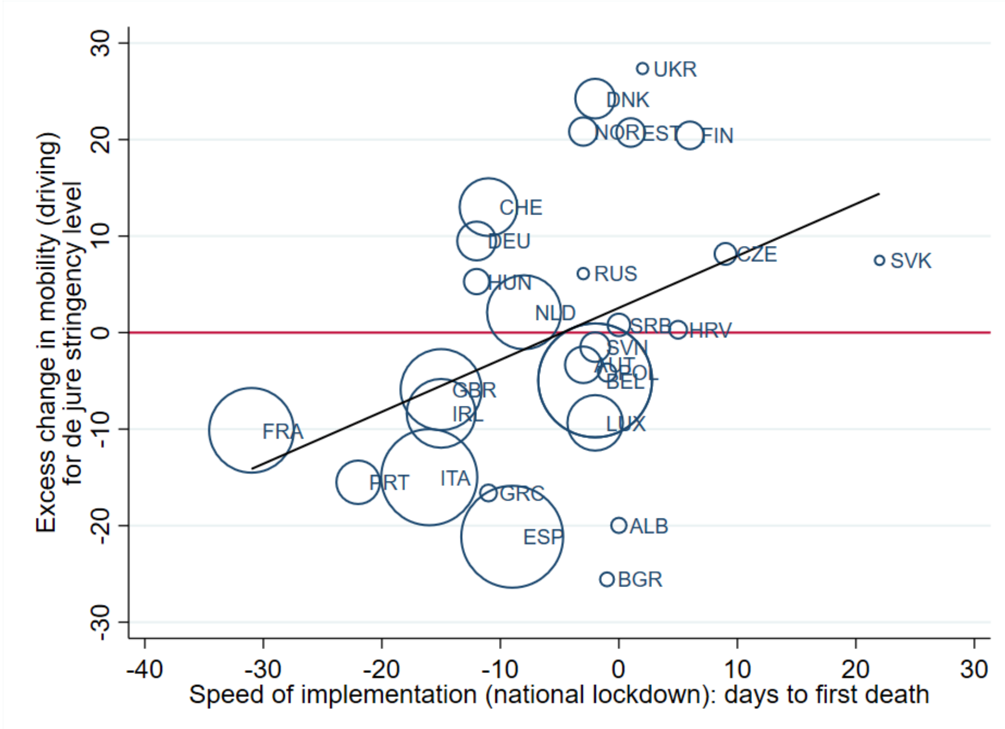
Note: this figure plots the relationship between the mean stringency of government response during the full lockdown (vertical axis) and the speed of implementation of the full lockdown (horizontal axis). The first variable is the mean value of government response stringency index during the period when a full lockdown was place. The index ranges from 0 (less stringent) to 100 (most stringent) and is calculated by a team at the Blavatnik School of Government (Oxford University). The index is based on policy decisions taken by governments in response to the COVID-19 pandemic. Data and methodology available in https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker. The speed of implementation of the full lockdown is calculated as the number of days to the first reported death by COVID-19 on the implementation date. A negative value indicates that the full lockdown was implemented after the first death was reported, a positive value indicates that the lockdown was implemented before the first death was reported. The black line plots the linear fit between the maximum stringency and the speed of implementation. The size of the bubbles is proportional to the mortality rate per million inhabitants as of April 25, 2020.

Figure A.2 – Change in mobility (driving) and maximum stringency of government response (Oxford BSG index)



Note: this figure plots the relationship between the change in mobility (driving) associated to the full lockdown (vertical axis) and the maximum stringency of government response (horizontal axis). The first variable is estimated as the difference in the mean mobility index for driving during the implementation of the national lockdown and the mean mobility index for driving during the pre-pandemic period (phase I: from January 13, 2020 to the day the first case was reported). The horizontal axis plots the mean value of the government response stringency index during the period when a full lockdown was place. The index ranges from 0 (less stringent) to 100 (most stringent) and is calculated by a team at the Blavatnik School of Government (Oxford University). The index is based on policy decisions taken by governments in response to the COVID-19 pandemic. Data and methodology available in https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker. The black line plots the linear fit between the change in mobility and the maximum stringency of government response. The size of the bubbles is proportional to the mortality rate per million inhabitants as of April 25, 2020.

<u>Figure A.3 – Excess change in mobility (driving) and speed of implementation</u>



Note: this figure plots the relationship between the excess change in mobility (driving) associated to the full lockdown for the given *de jure* stringency level (vertical axis) and the speed of implementation of the national lockdown (horizontal axis). The first variable is estimated as the difference in the predicted change in mobility for a given level of *de jure* stringency of lockdown (linear fit line in figure A.2). A positive value implies that the country's effective drop in mobility associated to the lockdown is smaller than the linear prediction given the *de jure* stringency of that country's lockdown. A negative value implies that the country's effective drop in mobility associated to the lockdown is larger than the linear prediction given the *de jure* stringency of that country's lockdown. *De jure* stringency is measured by the government response stringency index of Oxford BSG (see Appendix for a detailed definition).The horizontal axis plots the speed of implementation of the full lockdown, which is calculated as the number of days to the first reported death by COVID-19 on the implementation date. A negative value indicates that the full lockdown was implemented after the first death was reported, a positive value indicates that the lockdown was implemented before the first death was reported. The black line plots the linear fit between the excess change in mobility and the speed of implementation. The size of the bubbles is proportional to the mortality rate per million inhabitants as of April 25, 2020.

Appendix 2. Definition of NPI implementation dates

The main source for information on the implementation of NPIs is the data set compiled by Coronavirus Government Response Tracker of the Blavatnik School of Government at Oxford University (https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker). We use the version of the data set published on April 30, 2020. The following criteria were used to determine the implementation dates:

a) Cancelation of public events:

Indicator C3 takes a value of 2 ("require canceling")

b) School closure:
Indicator C1 takes a value of 3 ("require closing of all levels") or 2 ("require closing some levels") (and C1_Flag takes a value of 1 ("General")

c) Partial lockdown:
1) Indicator C2 ("workplace restrictions") takes a value of 2 ("require closing for some category of workers") or 3 ("require closing all-but-essential workplaces") and C2_Flag takes a value of 0 ("Targeted")
Or
2) Indicator C7 ("restrictions on internal movements") takes a value of 1 ("recommend movement restriction") and C2 takes a value of 2 ("require closing for some category of workers")

d) Full lockdown:
1) Indicator C2 ("workplace restrictions") takes a value of 2 ("require closing for some category of workers") or 3 ("require closing all-but-essential workplaces") and C2_Flag takes a value of 1 ("General")
Or
2) Indicator C7 ("restrictions on internal movements") takes a value of 2 ("movement restricted") and C2 takes a value of 2 ("require closing for some category of workers")

For countries not included in the Oxford Government Response Tracker, we used alternative sources, including news reports for full and partial lockdown measures and the World Bank Education COVID-19 Dashboard (https://www.worldbank.org/en/data/interactive/2020/03/24/world-bank-education-and-covid-19) for school closures. Table A.2 indicates the date of NPI implementation for each country.

Table A.2: NPI implementation dates by country.

Country	Cancelation of public events	School closure	Partial lockdown	Full lockdown
Albania	9-Mar-20	9-Mar-20	9-Mar-20	12-Mar-20
Armenia	24-Mar-20	13-Mar-20		24-Mar-20
Austria	11-Mar-20	16-Mar-20		16-Mar-20
Azerbaijan	14-Mar-20	3-Mar-20	22-Mar-20	31-Mar-20
Belarus				
Belgium	14-Mar-20	14-Mar-20		14-Mar-20
Bulgaria	13-Mar-20	5-Mar-20		13-Mar-20
Bosnia and Herzegovina	11-Mar-20	17-Mar-20		17-Mar-20
Croatia	10-Mar-20	14-Mar-20	14-Mar-20	20-Mar-20
Cyprus	10-Mar-20	13-Mar-20		16-Mar-20
Czech Republic	11-Mar-20	11-Mar-20		14-Mar-20
Denmark	16-Mar-20	13-Mar-20	13-Mar-20	18-Mar-20
Estonia	12-Mar-20	16-Mar-20		25-Mar-20
Finland	16-Mar-20	16-Mar-20	16-Mar-20	16-Mar-20
France	13-Mar-20	16-Mar-20		17-Mar-20
Georgia	31-Mar-20	2-Mar-20	19-Mar-20	31-Mar-20
Germany	10-Mar-20	16-Mar-20		22-Mar-20
Greece	9-Mar-20	11-Mar-20		23-Mar-20
Hungary	11-Mar-20	11-Mar-20	16-Mar-20	28-Mar-20
Iceland	24-Mar-20	17-Mar-20		
Ireland	12-Mar-20	12-Mar-20		27-Mar-20
Italy	23-Feb-20	4-Mar-20	8-Mar-20	10-Mar-20
Kazakhstan	12-Mar-20	16-Mar-20	19-Mar-20	30-Mar-20
Kosovo	24-Mar-20	12-Mar-20		24-Mar-20
Kyrgyz Republic	12-Mar-20	16-Mar-20	25-Mar-20	25-Mar-20
Lithuania	16-Mar-20	12-Mar-20		16-Mar-20
Luxembourg	13-Mar-20	16-Mar-20		16-Mar-20
Latvia	14-Mar-20	12-Mar-20	14-Mar-20	
Moldova	10-Mar-20	11-Mar-20		24-Mar-20
North Macedonia	18-Mar-20	10-Mar-20		18-Mar-20
Malta	22-Mar-20	17-Mar-20		22-Mar-20
Montenegro	30-Mar-20	13-Mar-20		30-Mar-20
Netherlands	10-Mar-20	15-Mar-20		15-Mar-20
Norway	12-Mar-20	12-Mar-20		16-Mar-20
Poland	10-Mar-20	12-Mar-20		14-Mar-20
Portugal	12-Mar-20	13-Mar-20	19-Mar-20	9-Apr-20
Romania	21-Mar-20	11-Mar-20		21-Mar-20
Russian Federation	10-Mar-20	23-Mar-20		30-Mar-20
Serbia	15-Mar-20	16-Mar-20	18-Mar-20	21-Mar-20
Slovak Republic	10-Mar-20	16-Mar-20	12-Mar-20	16-Mar-20
Slovenia	20-Mar-20	16-Mar-20	12-Mar-20	20-Mar-20
Spain	10-Mar-20	14-Mar-20		14-Mar-20
Sweden	12-Mar-20			
Switzerland	25-Feb-20	13-Mar-20		17-Mar-20
Tajikistan				
Turkey	16-Mar-20	16-Mar-20	22-Mar-20	
Turkmenistan				
United Kingdom	21-Mar-20	21-Mar-20	22-Mar-20	21-Mar-20
Ukraine	17-Mar-20	12-Mar-20		17-Mar-20
Uzbekistan	24-Mar-20	16-Mar-20		24-Mar-20

Appendix 3. Estimation of the short-term elasticity between NO_2 emissions and economic activity: The case of China

Vehicles, power plants, and industrial facilities that use fossil fuels as energy emit substantial amounts of nitrogen dioxide (NO_2) as a byproduct of their activity. In this appendix section, we provide a simple calculation of the elasticity between such measurements and actual economic indicators recently published by China for the period January-February 2020. This elasticity can be understood as an “exchange rate” between NO_2 emissions and economic activity, which can then allow for a high-frequency estimate of economic activity. Note that the elasticity we intend to estimate is short-term – it does not relate to long-term trends between emissions and growth, where technological changes may play a more considerable role than short-term economic disruptions.

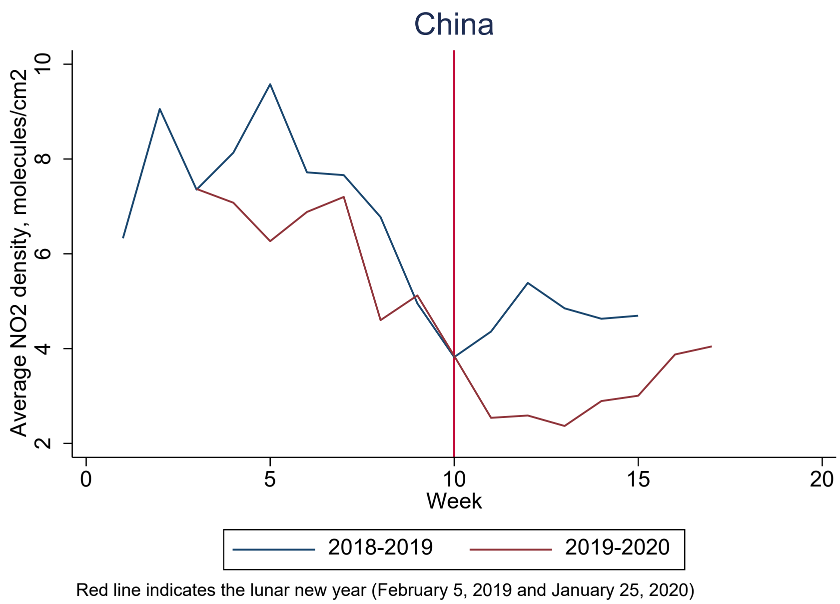
The COVID-19 outbreak in the city of Wuhan led the Chinese government to impose a lockdown in the city on January 23, 2020, later extended to most of Hubei province on the following day, the whole province being on lockdown by January 28. The lockdown was lifted for parts of Hubei on March 13 and for Wuhan on April 8. The lockdown of Hubei coincided with the Lunar New Year holiday, which the Chinese government decided to extend for ten days (instead of the regular seven days) up to February 2 for all the country, with normal work expected to resume by February 3. However, provincial authorities delayed the resumption of normal work to February 10 throughout most of China (except Hubei).

The economic disruption driven by the extension of the Lunar New Year holiday, the lockdown in Hubei and the mobility restrictions imposed in light of the spread of COVID-19 is evident when looking at the emissions of NO_2 in China. Figure A.4 plots the evolution of the average NO_2 concentration in the air of the country[24] over two periods of 14 weeks centered around the Lunar New Year in 2019 (February 5) and 2020 (January 25). While in the lead up to the Lunar New Year the NO_2 was similar or slightly lower in 2020 than in 2019, after that date the emissions rebounded in 2019 but fell to lower levels in 2020. In the three weeks that followed the Lunar New Year holiday week, the average concentration of NO_2 in 2019 (4.87×10^{15} molecules/cm^2) was almost at the same level as in the last week before the holiday (4.95×10^{15} molecules/cm^2), while in 2020 it was at half its level (an average of 2.50×10^{15} molecules/cm^2 vs a pre-holiday week average of 5.12×10^{15} molecules/cm^2). The levels of NO_2 in 2020 only started increasing in the fourth week after the Lunar New Year holiday. Overall, in the three weeks before the Lunar New Year,

[24] Given the very low population density of China’s western half, only 50% of the surface of the country is used for this calculation. Data pixels (0.25 degree x 0.25 degree) for the whole Chinese territory are ordered based on their mean NO_2 concentration in the 14 weeks of 2019 under consideration and the 50% with lowest values are dropped for the analysis.

the average concentration of NO_2 in 2020 was 89% of the same value in 2019, while for the three weeks after the holiday the average value in 2020 was 53% of the 2019 value.

Figure A.4 – Average NO_2 concentration in China, 2019 and 2020



Note: this figure plots the value of average weekly NO_2 density over Chinese territory (see note 14 before for precisions on this calculation) in December-February of years 2018-2019 and 2019-2020. The values corresponding to 2019-2020 have been shifted so the lunar new year coincides with year 2018-2019 (week 10 of 2019).

China's National Bureau of Statistics has recently published consolidated economic indicators for the period January-February 2020. The value-added of industrial enterprises fell 13.5% on a year-to-year basis, while the index of services production dropped 13% in the same period. Total retail sales of consumer goods decreased by 20.5% when compared to the same two months of 2019. Separately, the Financial Times has created an index of daily economic activity for China,[25] showing that by mid-February 2020, economic activity was close to 50% below its value on January 1, 2020. The same index calculated for the equivalent period of 2019 was around 85% of the value of early 2020, suggesting a close to 40% year-to-year decrease in activity in mid-February 2020.

Table A.3 presents the calculation of a series of implied elasticities between NO_2 concentration and economic activity based on different economic indicators. The benchmark against which NO_2 concentration values in 2020 are compared corresponds to the average ratio between the three weeks before the Lunar New Year in 2020 and the same period in 2019 – this to take into account of the fact that, for reasons beyond

[25] See https://www.ft.com/content/0c13755a-6867-11ea-800d-da70cff6e4d3 Data only available by visual inspection.

this analysis, the NO_2 concentration in China had been slightly lower in 2020 than in 2019 even before any lockdown was imposed. Three economic indicators are expressed in bi-monthly terms, and therefore a comparable NO_2 concentration is calculated over two months, while one indicator (FT China Economic Activity Index) is expressed in weekly terms. The implied elasticities range from 0.32 in the case of industrial value-added to 1 for the FT China Economic Activity Index. This suggests considerable variability in the relationship between NO_2 concentration and economic activity. Despite this, the calculated elasticities allow estimating the potential economic consequences of lockdown-induced decreases in NO_2 concentration.

A cleaner exercise would have relied exclusively on data from areas where a strict lockdown was imposed –like the province of Hubei– in order to ensure that observed variations in emissions are driven by the same factors as those explaining the variations in economic indicators. While NO_2 concentration data are available for that province, no economic indicator has been yet published at that level, therefore making it impossible to estimate the corresponding elasticity. The elasticities calculated in table A.3 could, therefore, be biased by the presence of non-lockdown-induced variations in NO_2 concentration but, given the widespread economic disruption beyond the province of Hubei, this bias can be thought of as being small in relative magnitude.

Table A.3 – Calculation of elasticities between NO_2 concentration and economic activity

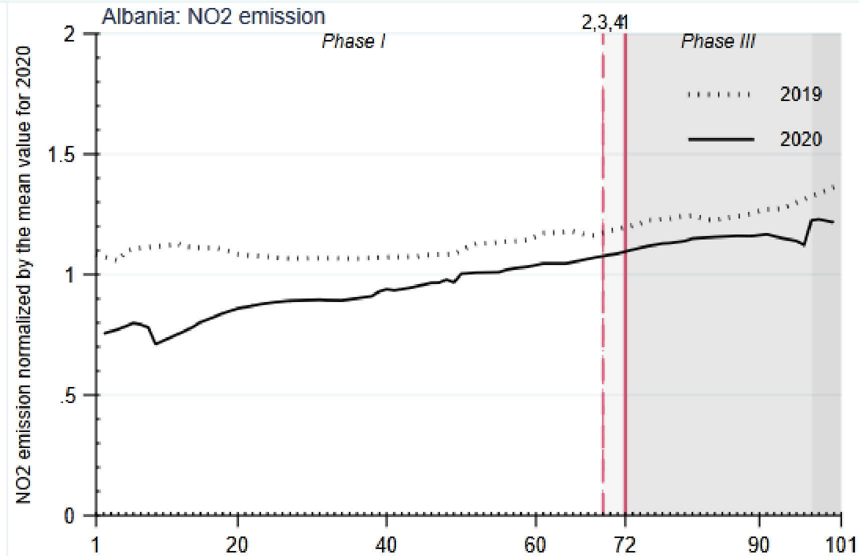
Average NO_2 concentration Benchmark: 3 weeks pre-lunar new year, ratio of 2020 vs 2019 (1)	Period (2)	Ratio vs 2019 (3)	Difference with benchmark (4)	Economic activity Indicator (5)	Difference with 2019 (6)	Implied elasticity (7)
0.89	January-February 2020	0.62	-31%	Value added in industrial enterprises	-13%	0.32
				Index of services production	-13.5%	0.33
				Retail sales of consumer goods	-20.5%	0.50
	3 weeks post lunar new year	0.53	-41%	FT China economic activity index (mid Feb)	-40%	1.00

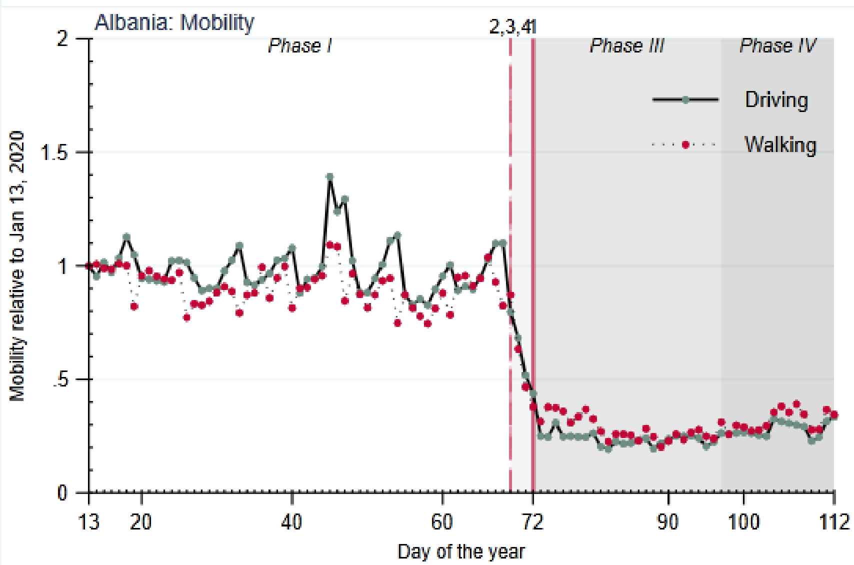
Note: this table presents the calculation of elasticities between NO_2 density over Chinese territory (columns 1 to 4) and short-term economic indicators (columns 5 and 6). The elasticities in column 7 are calculated as the ratio of the values in column 6 to the corresponding values in column 4.

Appendix 4

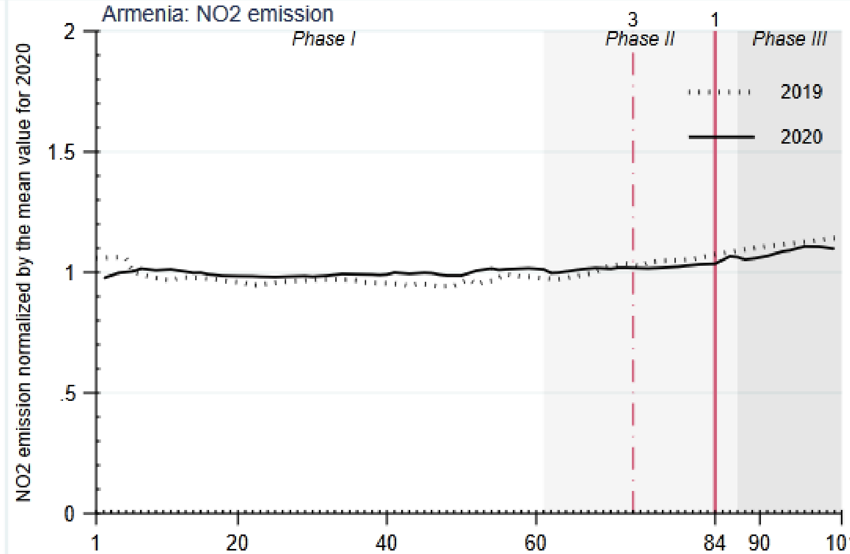
Individual country statistics

Albania


Albania: NO2 emission
2,3,4
1
Phase I
Phase III
2019
2020
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
1
20
40
60
72
90
101

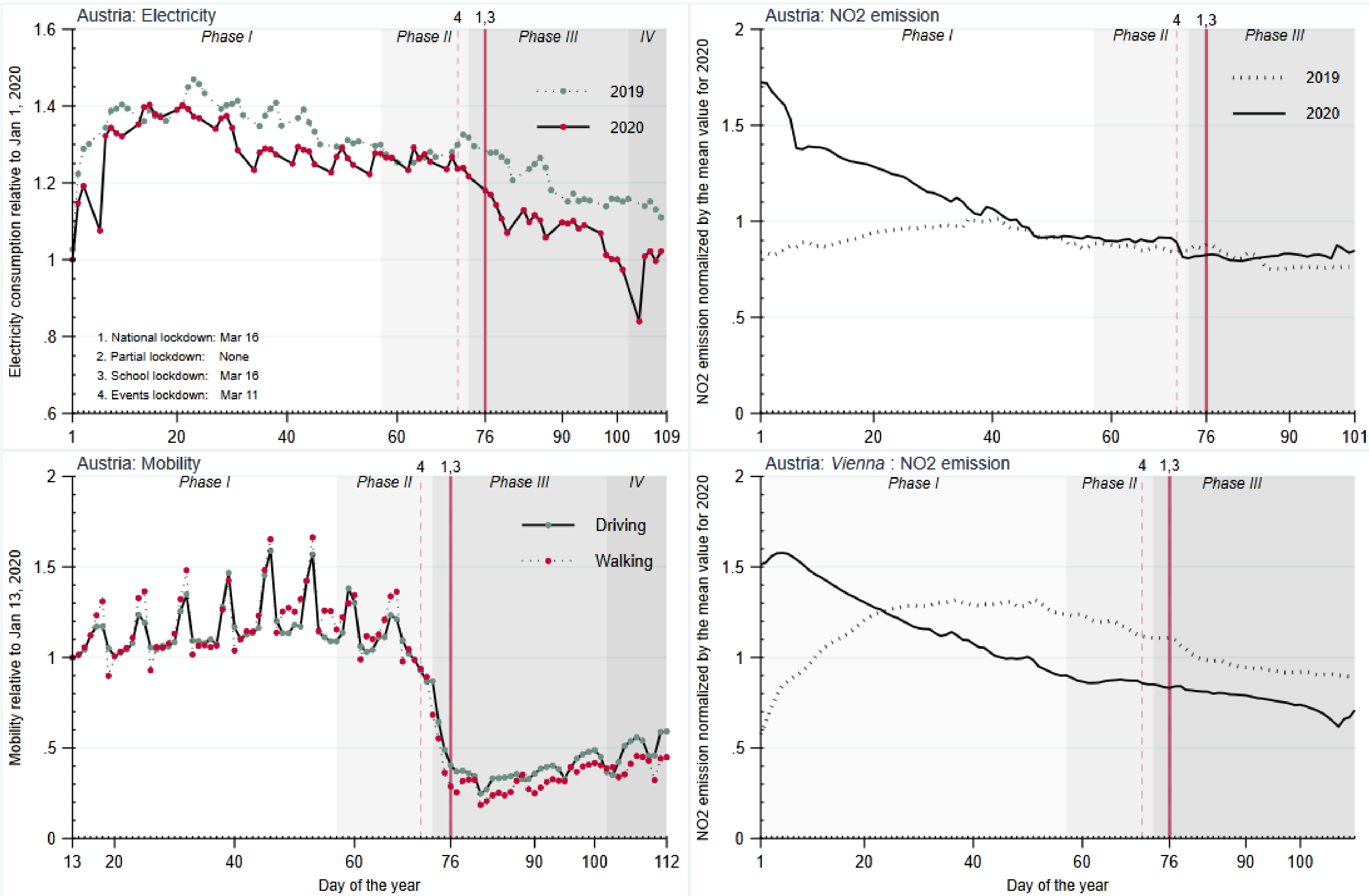

Albania: Mobility
2,3,4
1
Phase I
Phase III
Phase IV
Driving
Walking
Mobility relative to Jan 13, 2020
2
1.5
1
.5
0
13
20
40
60
72
90
100
112
Day of the year

Armenia

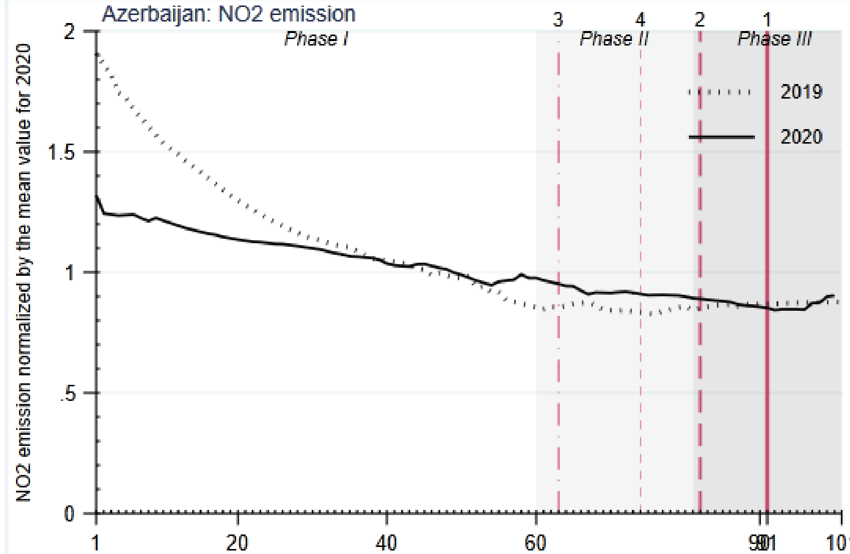


Armenia: NO2 emission
NO2 emission normalized by the mean value for 2020
Phase I
Phase II
Phase III
3
1
2019
2020
2
1.5
1
.5
0
1
20
40
60
84
90
101

Austria

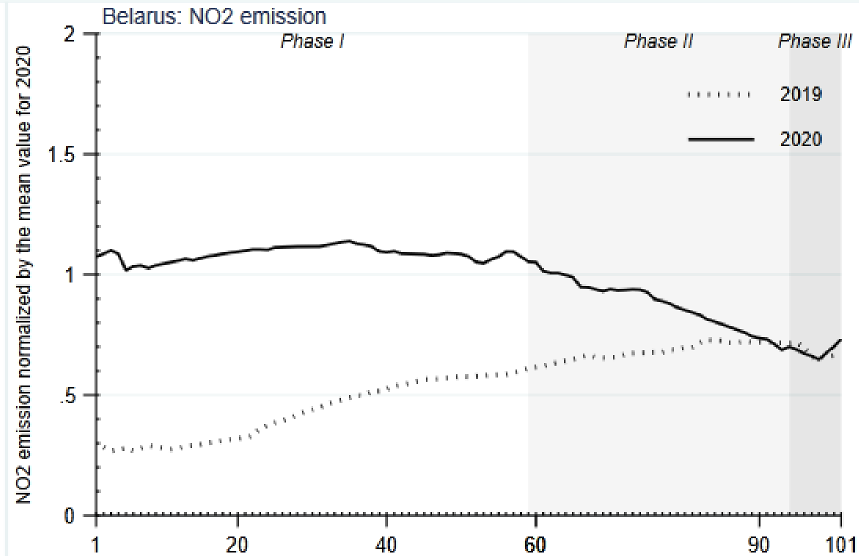

Austria: Electricity
Phase I
Phase II
Phase III
IV
4
1,3
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 16
2. Partial lockdown: None
3. School lockdown: Mar 16
4. Events lockdown: Mar 11
Austria: NO2 emission
NO2 emission normalized by the mean value for 2020
Austria: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Austria: Vienna : NO2 emission

Azerbaijan

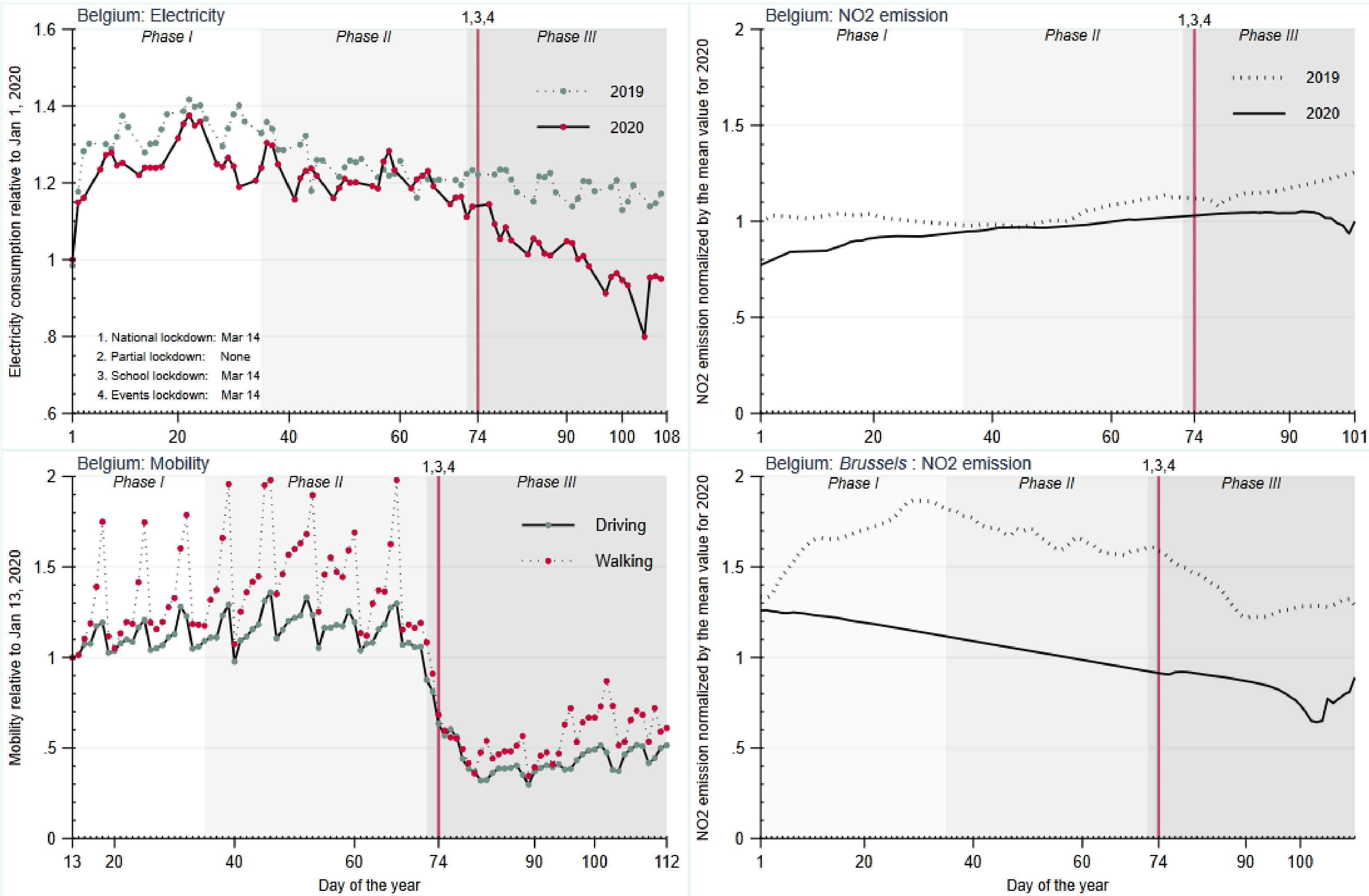


Azerbaijan: NO2 emission
NO2 emission normalized by the mean value for 2020
Phase I
Phase II
Phase III
3
4
2
1
2019
2020
2
1.5
1
.5
0
1
20
40
60
90
91
101

Belarus

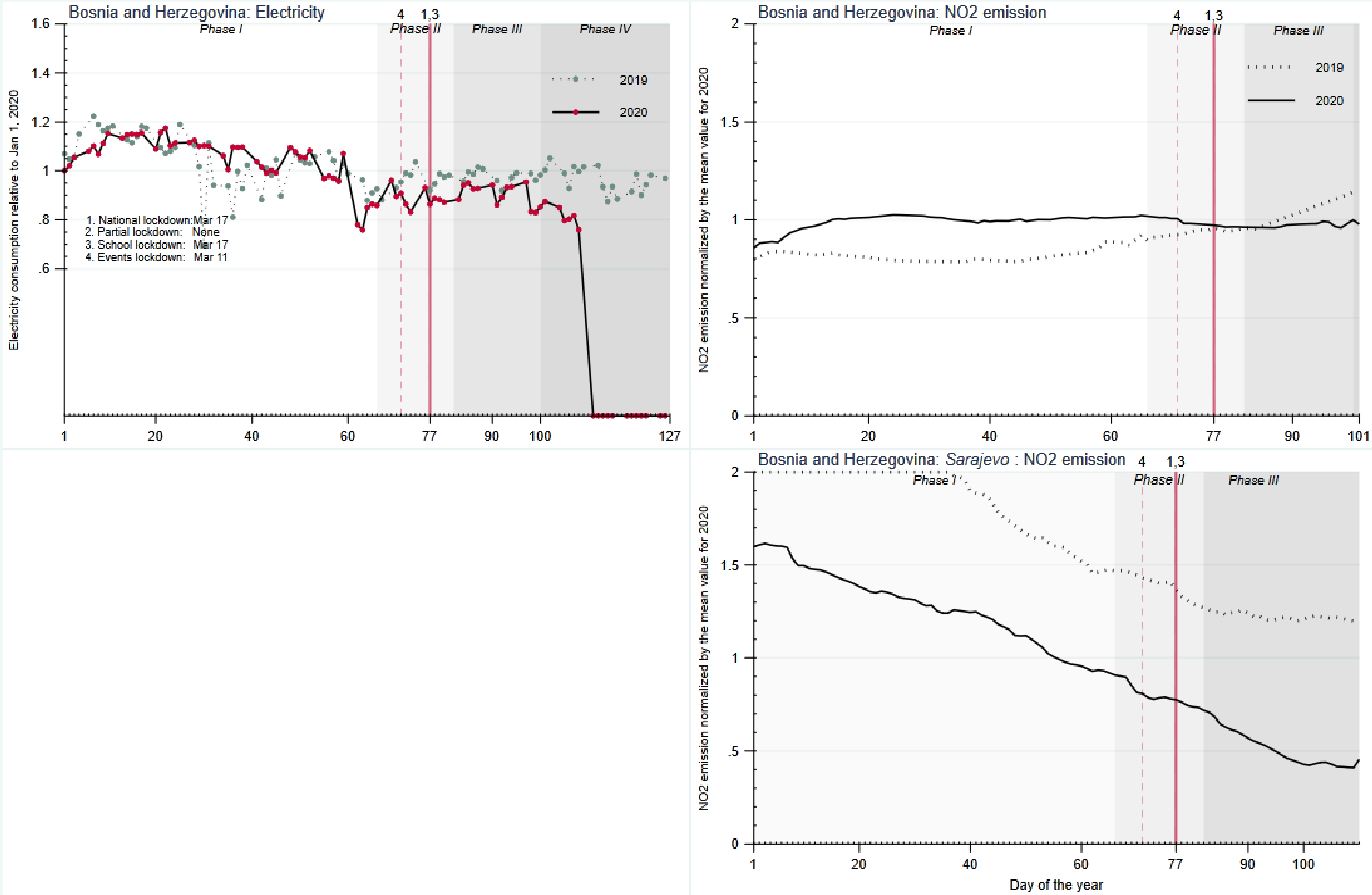

Belarus: NO2 emission
Phase I
Phase II
Phase III
2019
2020
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
1
20
40
60
90
101

Belgium

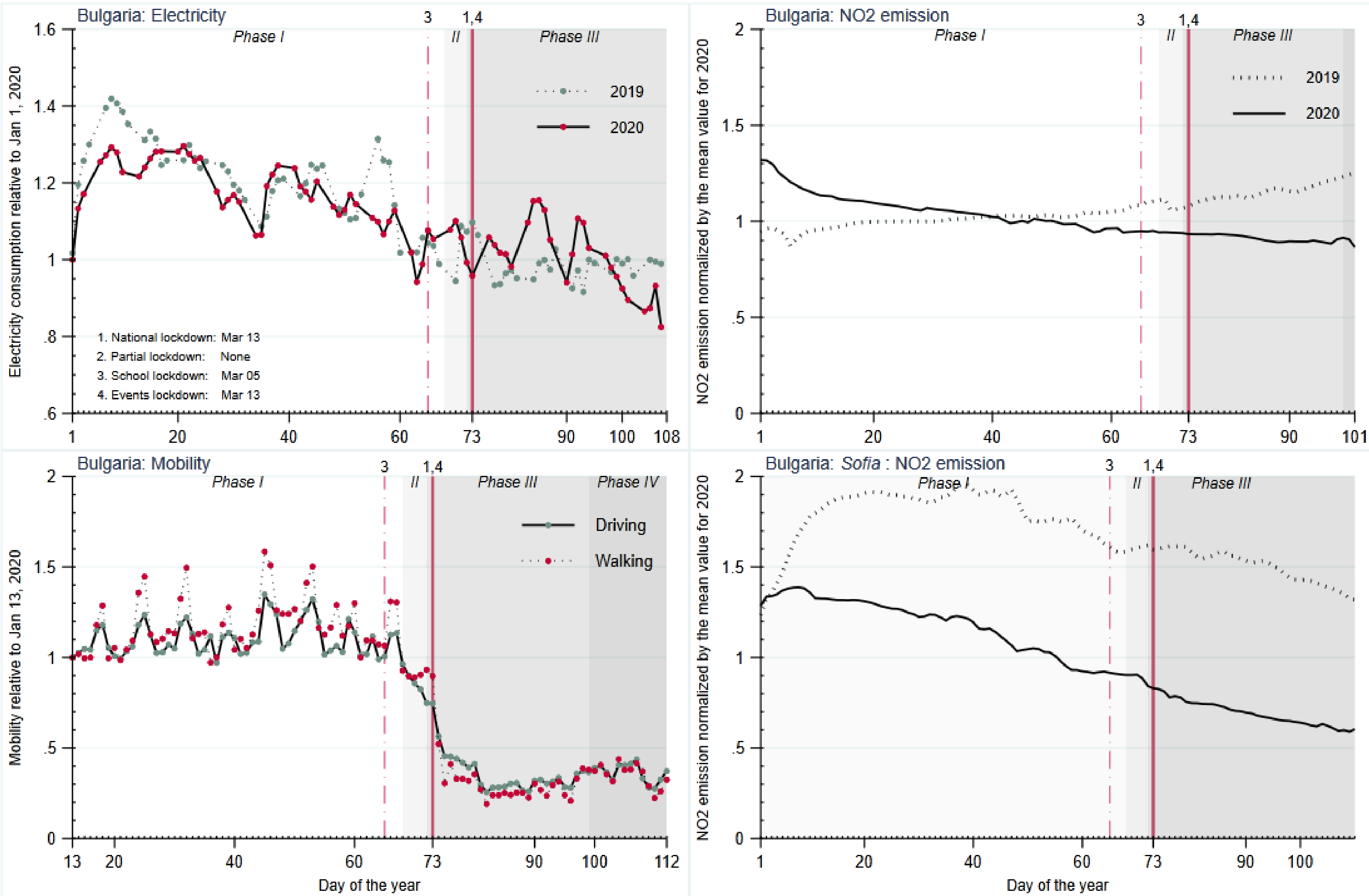


Belgium: Electricity
Phase I
Phase II
Phase III
1,3,4
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 14
2. Partial lockdown: None
3. School lockdown: Mar 14
4. Events lockdown: Mar 14
1.6
1.4
1.2
1
.8
.6
1
20
40
60
74
90
100
108
Belgium: NO2 emission
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
101
Belgium: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
13
112
Day of the year
Belgium: Brussels : NO2 emission

Bosnia and Herzegovina

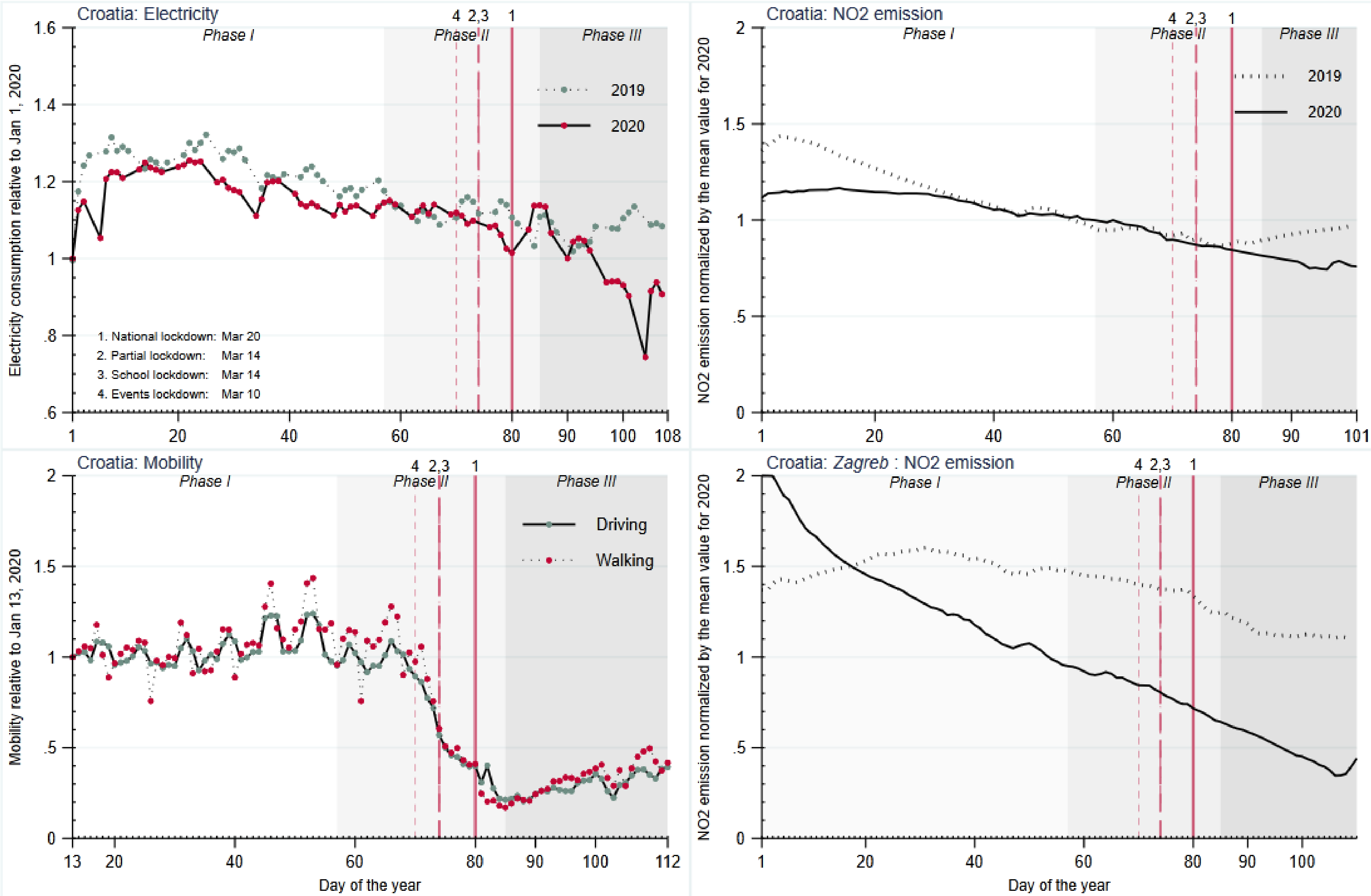


Bulgaria



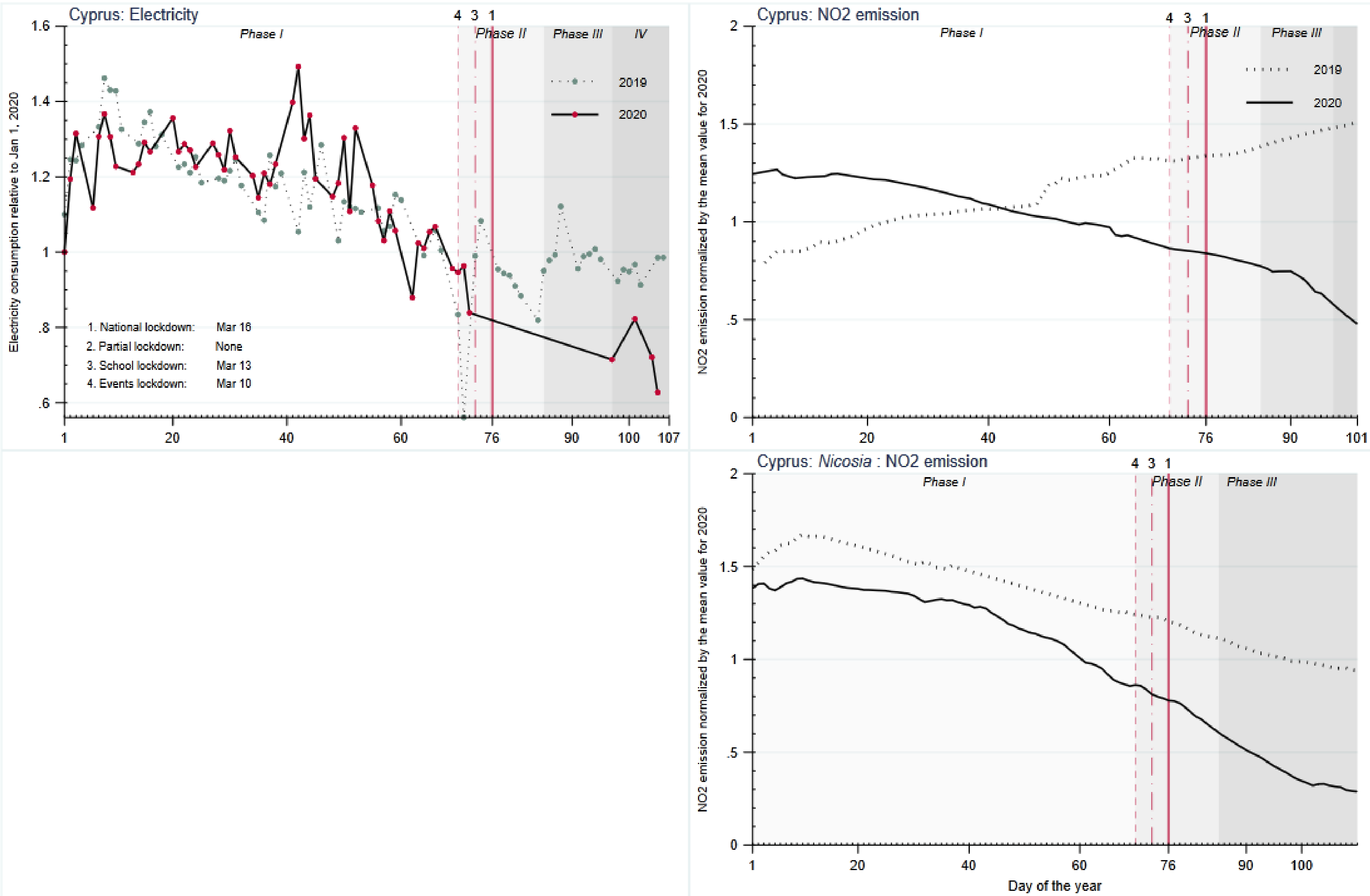
Bulgaria: Electricity
Phase I
II
Phase III
3
1,4
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 13
2. Partial lockdown: None
3. School lockdown: Mar 05
4. Events lockdown: Mar 13
Bulgaria: NO2 emission
NO2 emission normalized by the mean value for 2020
Bulgaria: Mobility
Phase IV
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Bulgaria: Sofia : NO2 emission

Croatia



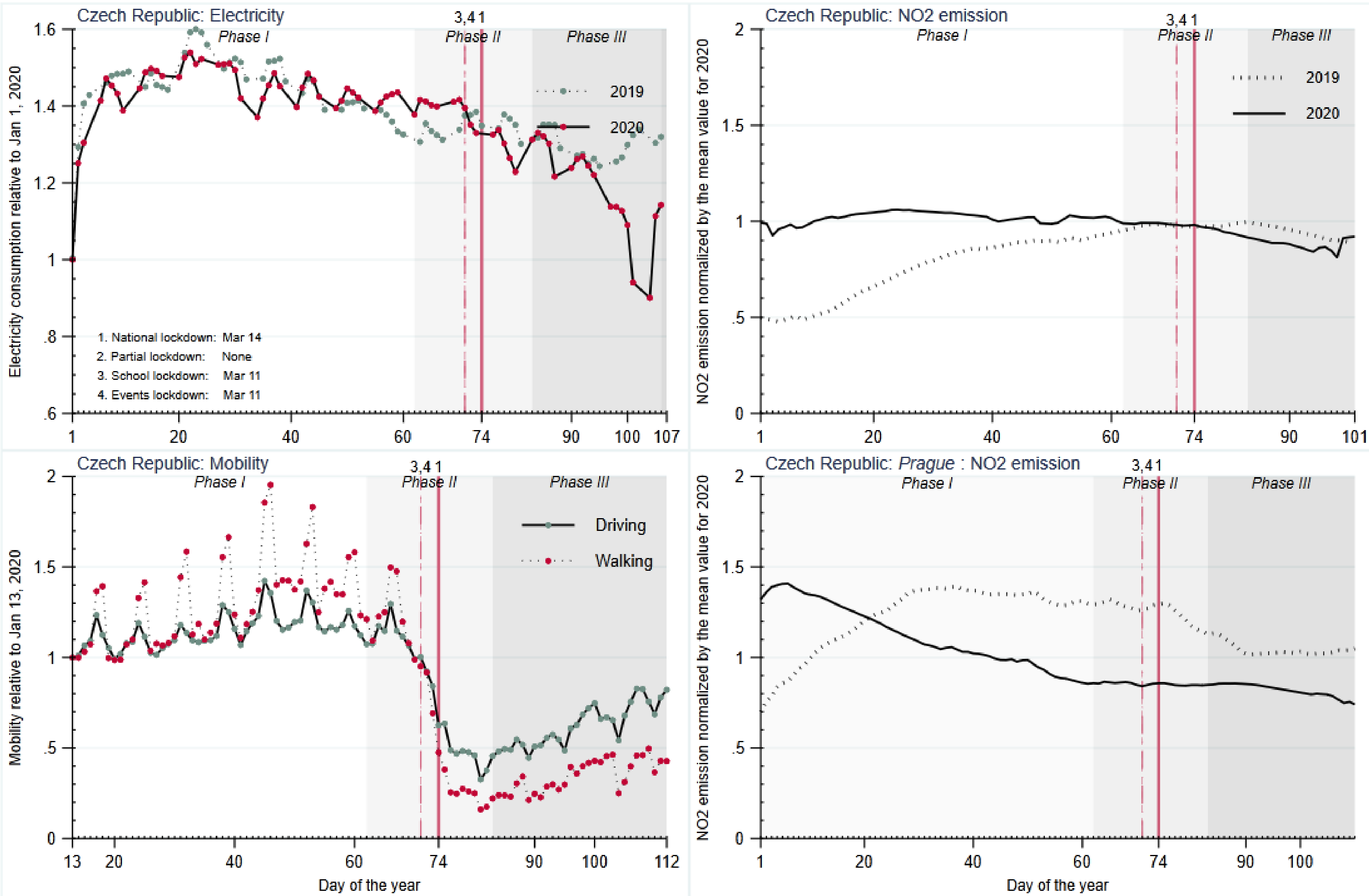
Croatia: Electricity
Phase I
Phase II
Phase III
4 2,3 1
2019
2020
1. National lockdown: Mar 20
2. Partial lockdown: Mar 14
3. School lockdown: Mar 14
4. Events lockdown: Mar 10
Electricity consumption relative to Jan 1, 2020
Croatia: NO2 emission
NO2 emission normalized by the mean value for 2020
Croatia: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Croatia: *Zagreb* : NO2 emission

Cyprus

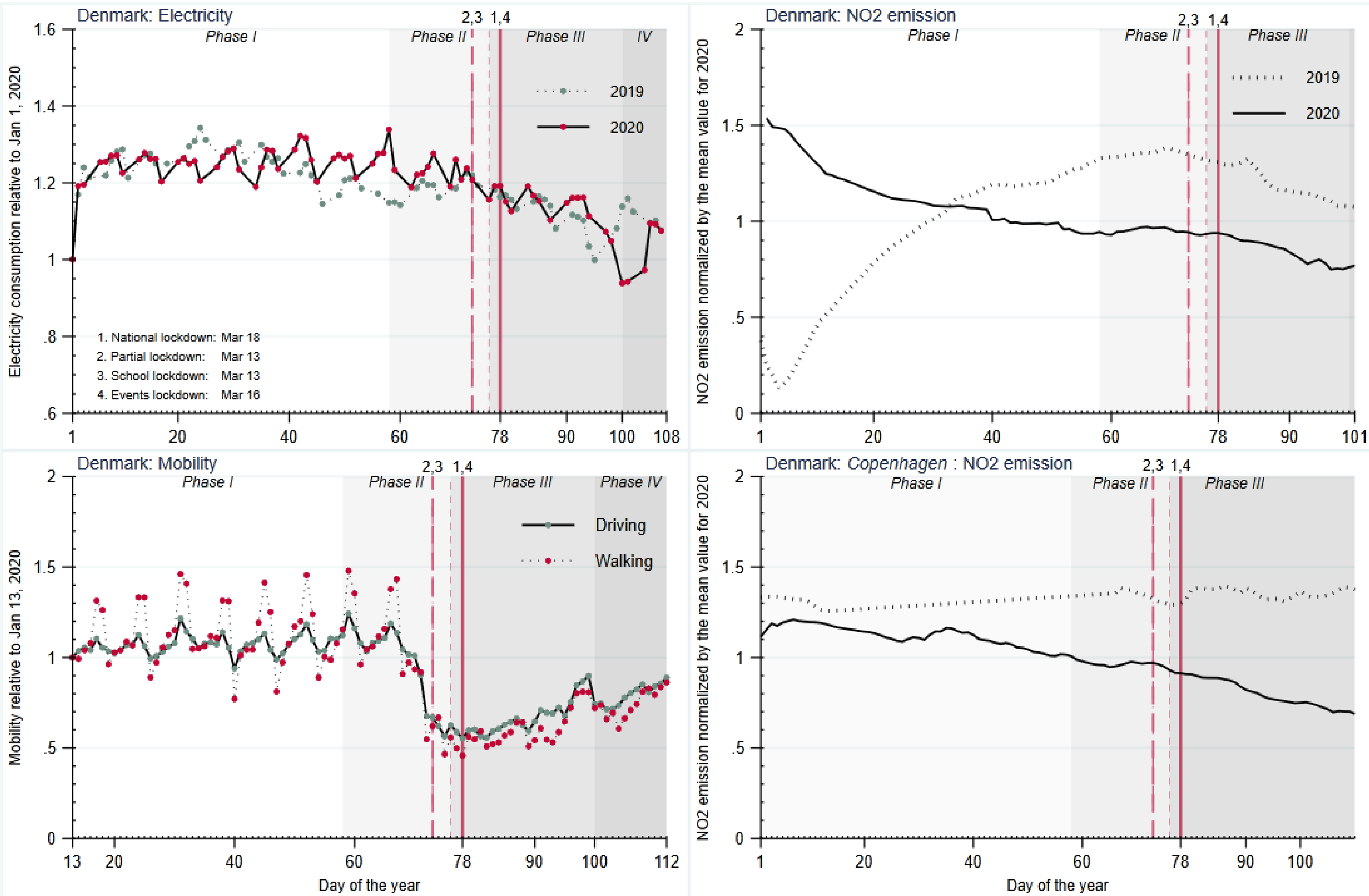


Cyprus: Electricity
Phase I
Phase II
Phase III
IV
4 3 1
2019
2020
1. National lockdown: Mar 16
2. Partial lockdown: None
3. School lockdown: Mar 13
4. Events lockdown: Mar 10
Electricity consumption relative to Jan 1, 2020
Cyprus: NO2 emission
NO2 emission normalized by the mean value for 2020
Cyprus: Nicosia : NO2 emission
Day of the year

Czech Republic

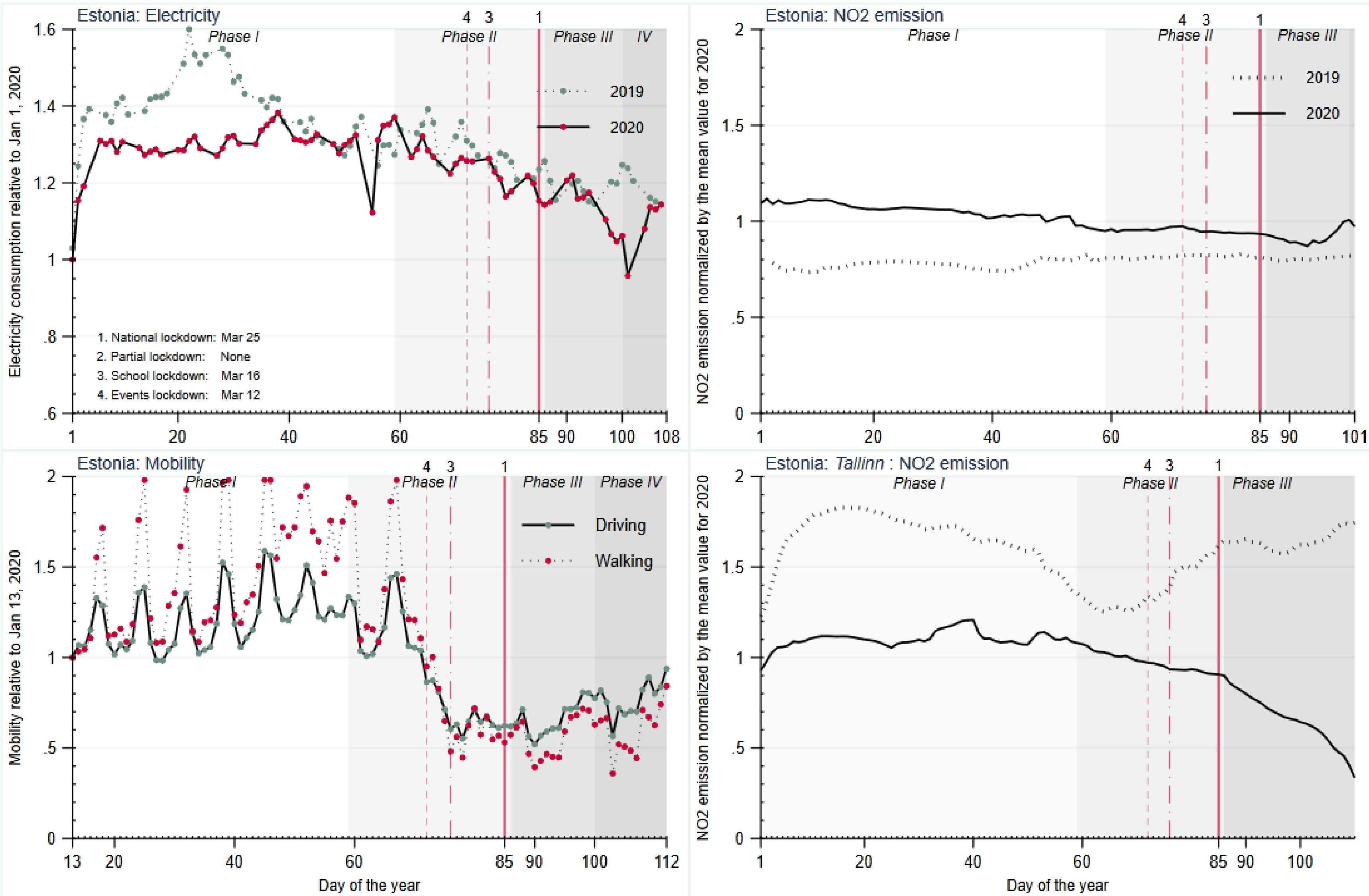


Denmark



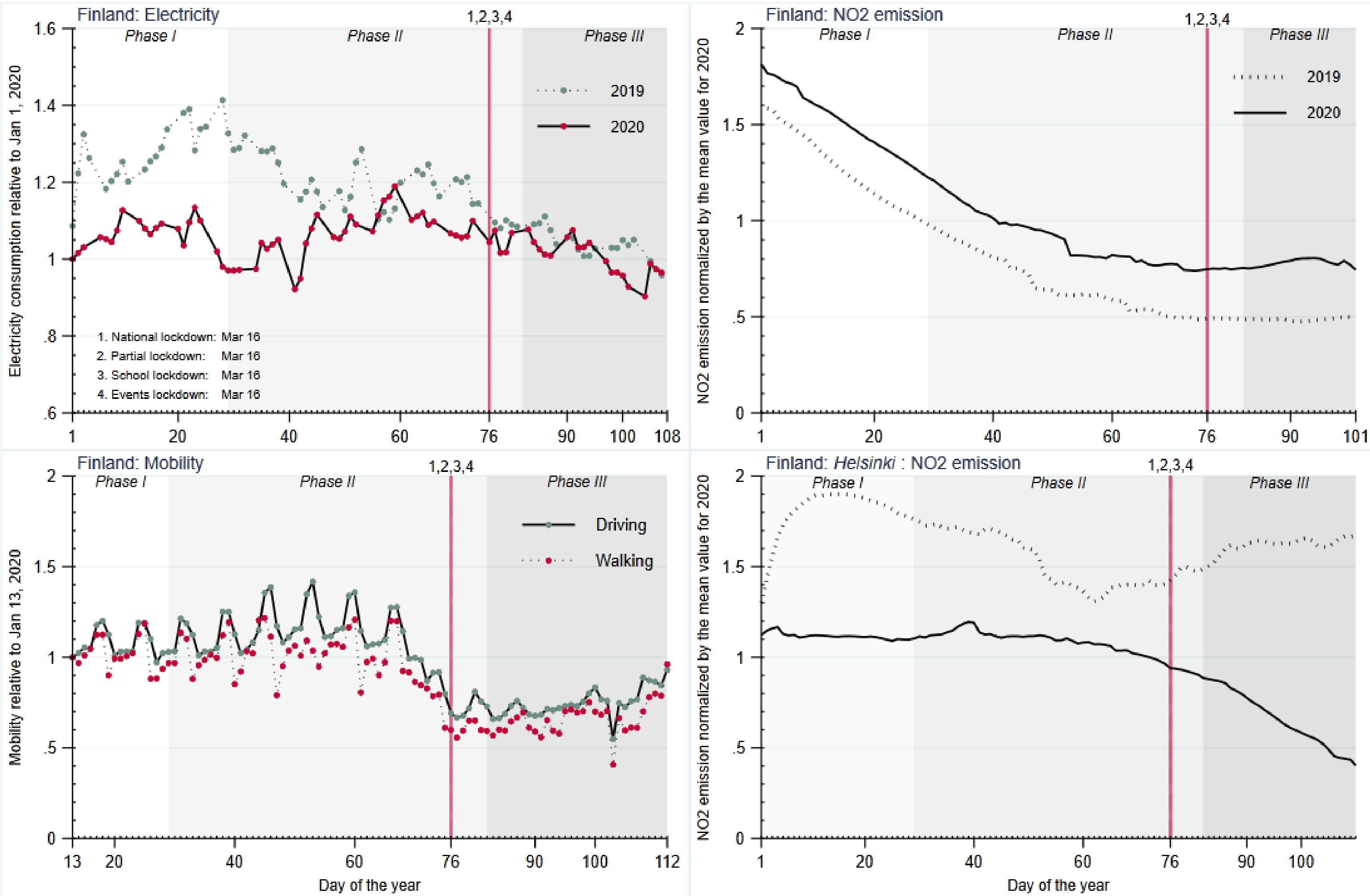
Denmark: Electricity
Phase I
Phase II
Phase III
IV
2,3 1,4
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 18
2. Partial lockdown: Mar 13
3. School lockdown: Mar 13
4. Events lockdown: Mar 16
Denmark: NO2 emission
NO2 emission normalized by the mean value for 2020
Denmark: Mobility
Phase IV
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Denmark: Copenhagen : NO2 emission

Estonia



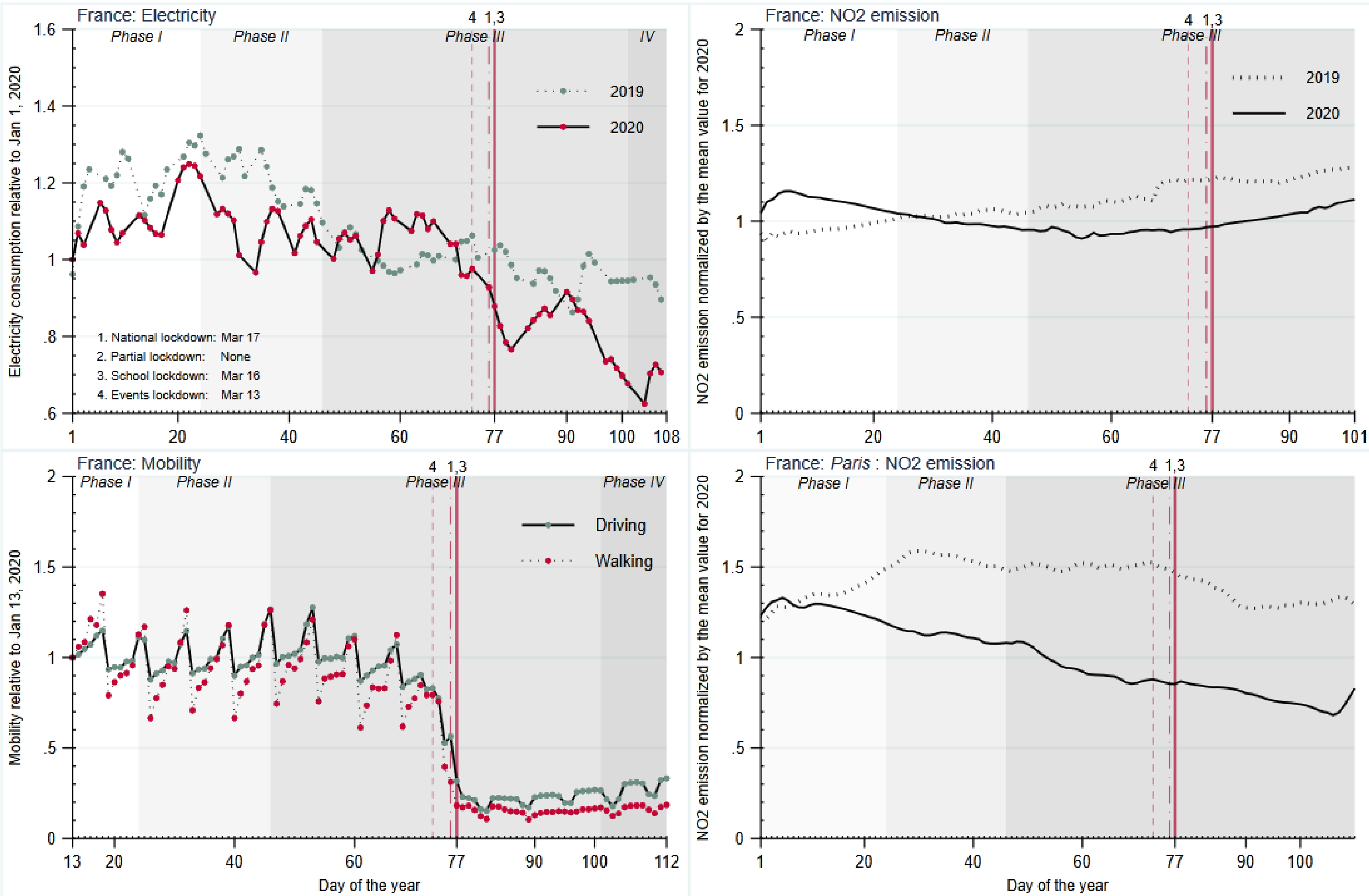
Estonia: Electricity
Phase I
Phase II
Phase III
IV
4
3
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 25
2. Partial lockdown: None
3. School lockdown: Mar 16
4. Events lockdown: Mar 12
Estonia: NO2 emission
NO2 emission normalized by the mean value for 2020
Estonia: Mobility
Phase IV
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Estonia: Tallinn : NO2 emission

Finland

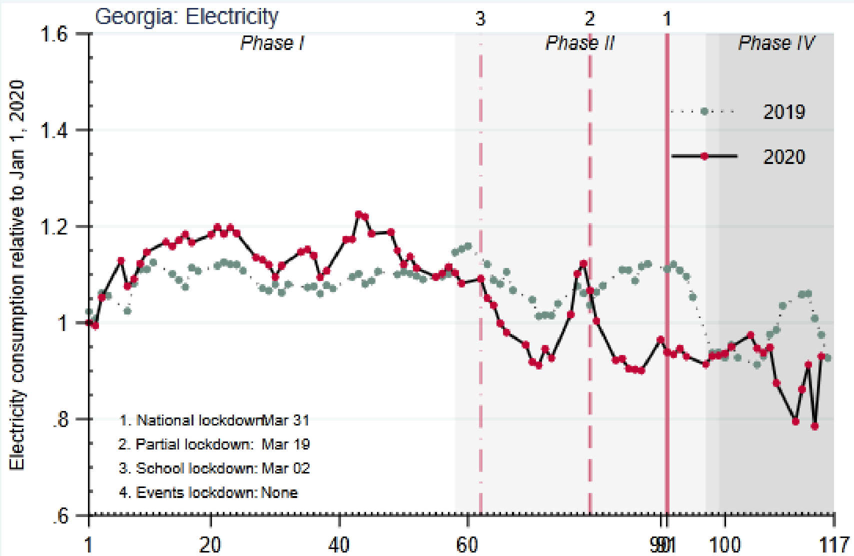


Finland: Electricity
1,2,3,4
Phase I
Phase II
Phase III
2019
2020
1. National lockdown: Mar 16
2. Partial lockdown: Mar 16
3. School lockdown: Mar 16
4. Events lockdown: Mar 16
Electricity consumption relative to Jan 1, 2020
Finland: NO2 emission
NO2 emission normalized by the mean value for 2020
Finland: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Finland: Helsinki : NO2 emission

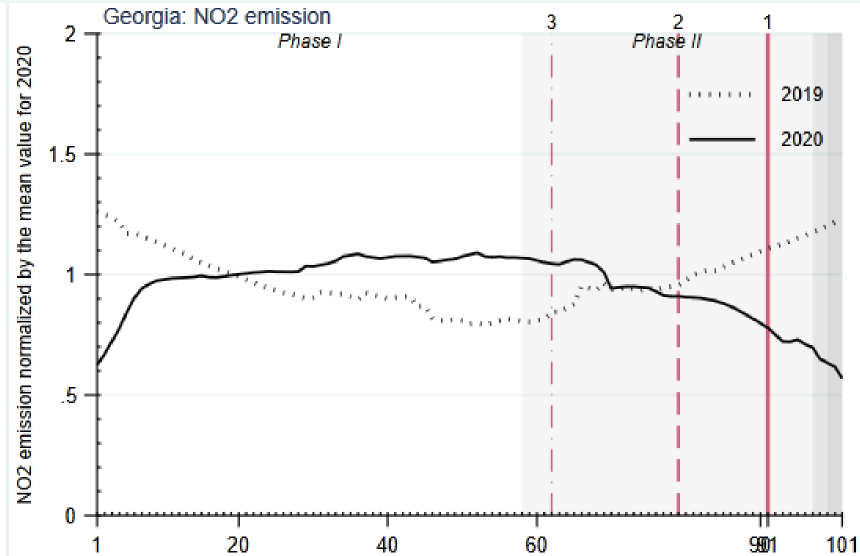
France


France: Electricity
Electricity consumption relative to Jan 1, 2020
Phase I
Phase II
Phase III
IV
4 1,3
2019
2020
1. National lockdown: Mar 17
2. Partial lockdown: None
3. School lockdown: Mar 16
4. Events lockdown: Mar 13
France: NO2 emission
NO2 emission normalized by the mean value for 2020
France: Mobility
Mobility relative to Jan 13, 2020
Phase IV
Driving
Walking
Day of the year
France: Paris : NO2 emission

Georgia

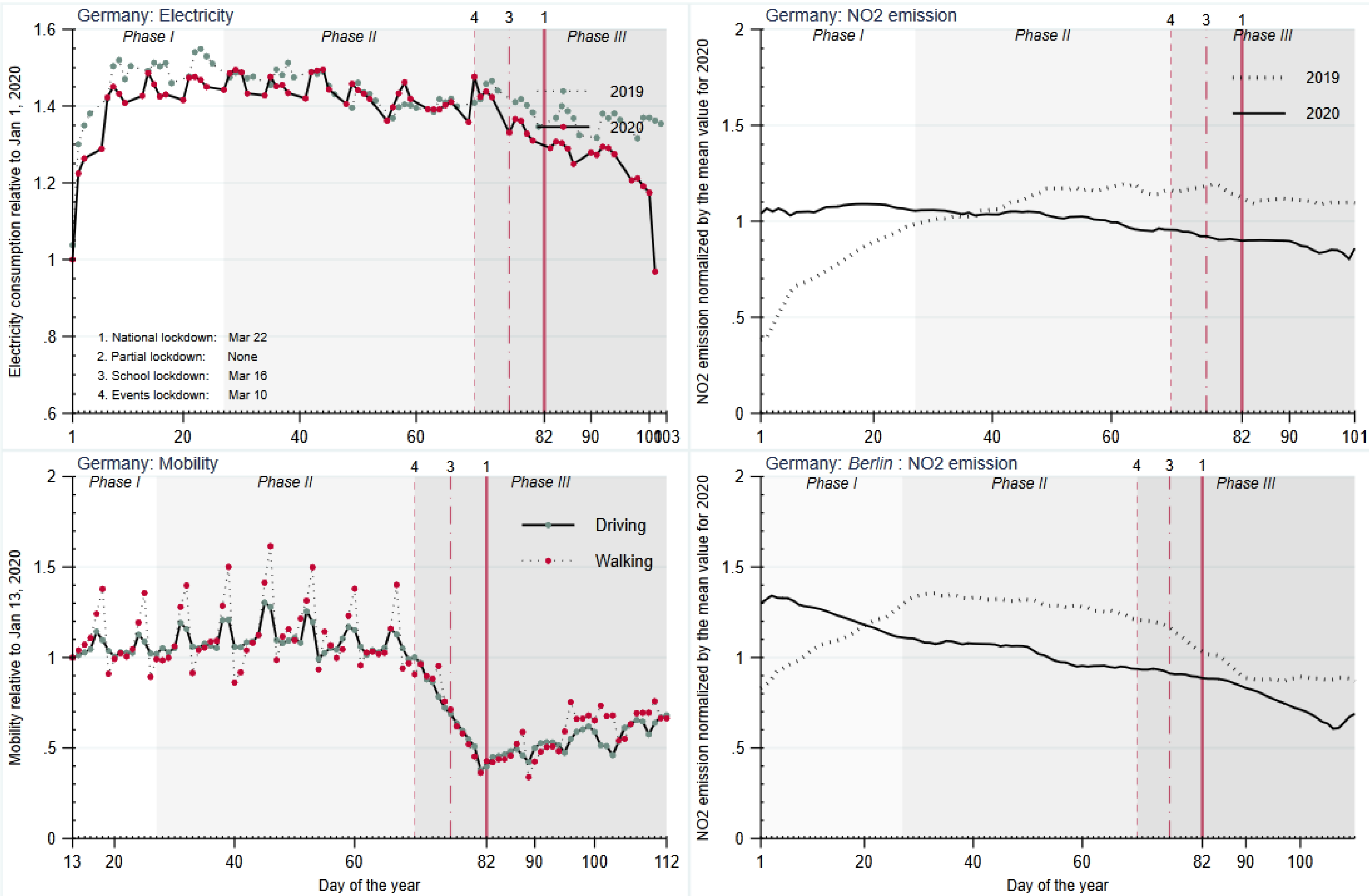


Georgia: Electricity
Phase I
Phase II
Phase IV
3
2
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 31
2. Partial lockdown: Mar 19
3. School lockdown: Mar 02
4. Events lockdown: None
1.6
1.4
1.2
1
.8
.6
1
20
40
60
90
91
100
117



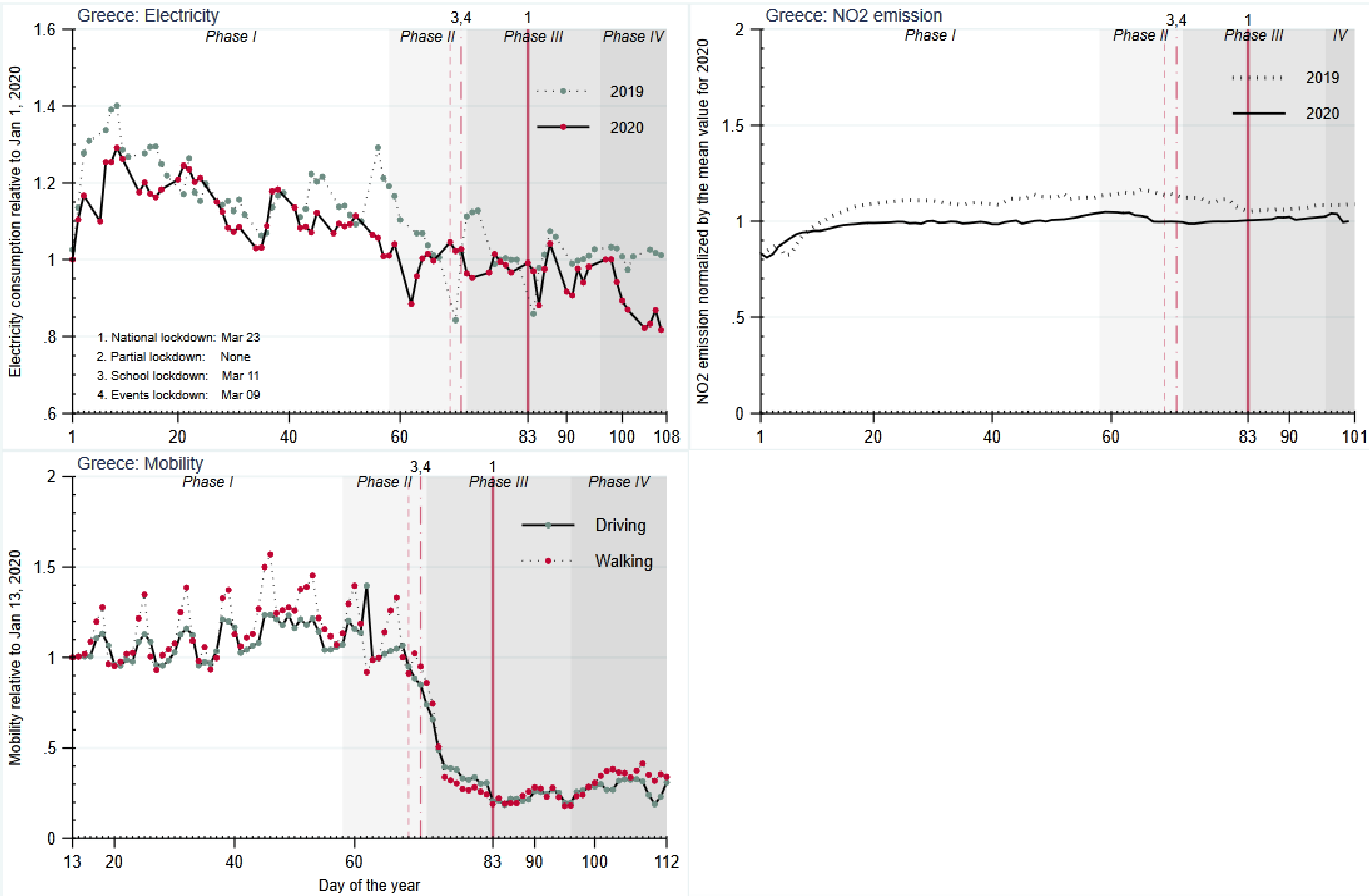
Georgia: NO2 emission
Phase I
Phase II
3
2
1
2019
2020
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
1
20
40
60
90
91
101

Germany

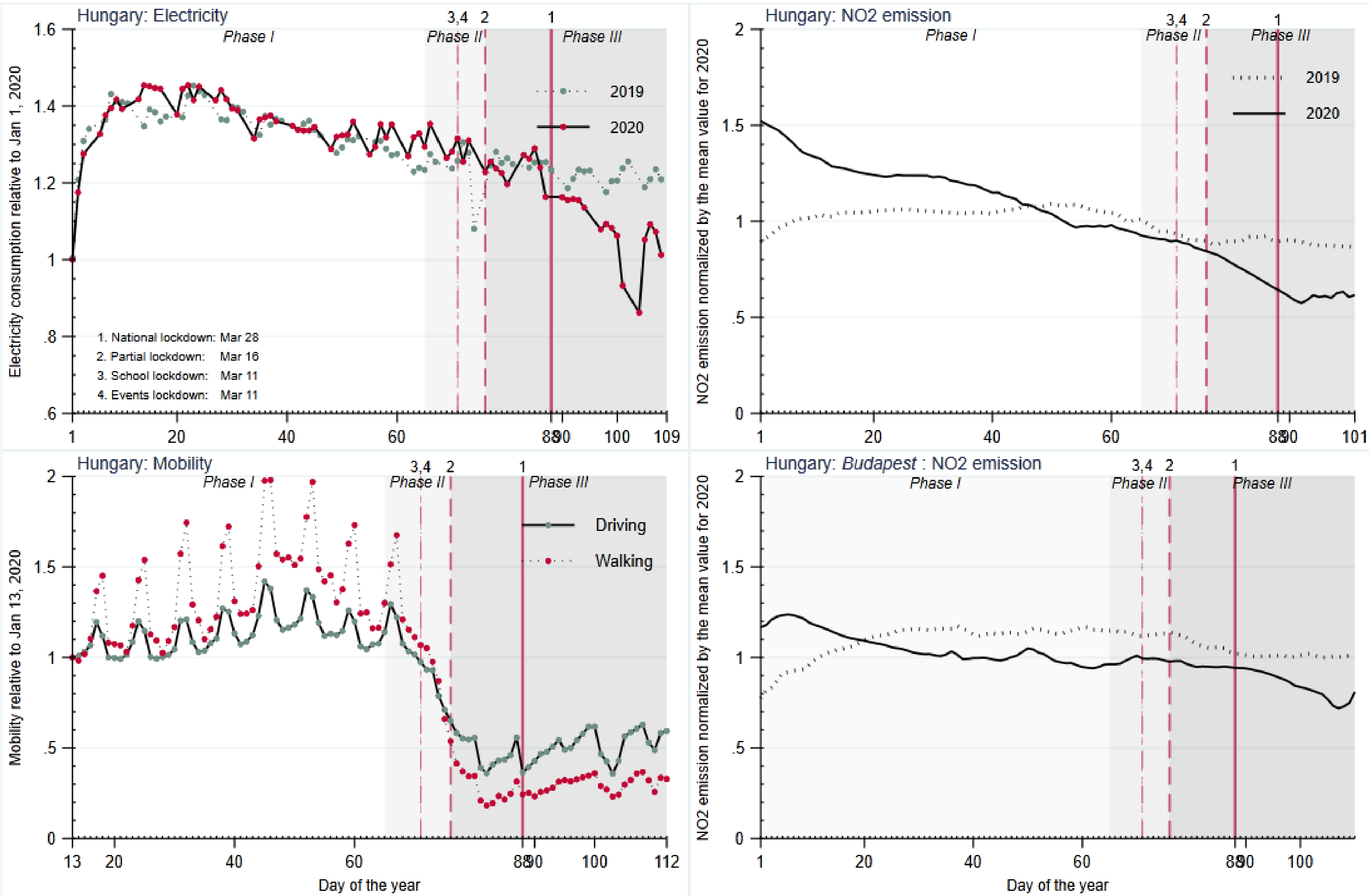


Germany: Electricity
Phase I
Phase II
Phase III
4
3
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 22
2. Partial lockdown: None
3. School lockdown: Mar 16
4. Events lockdown: Mar 10
Germany: NO2 emission
NO2 emission normalized by the mean value for 2020
Germany: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Germany: Berlin : NO2 emission

Greece

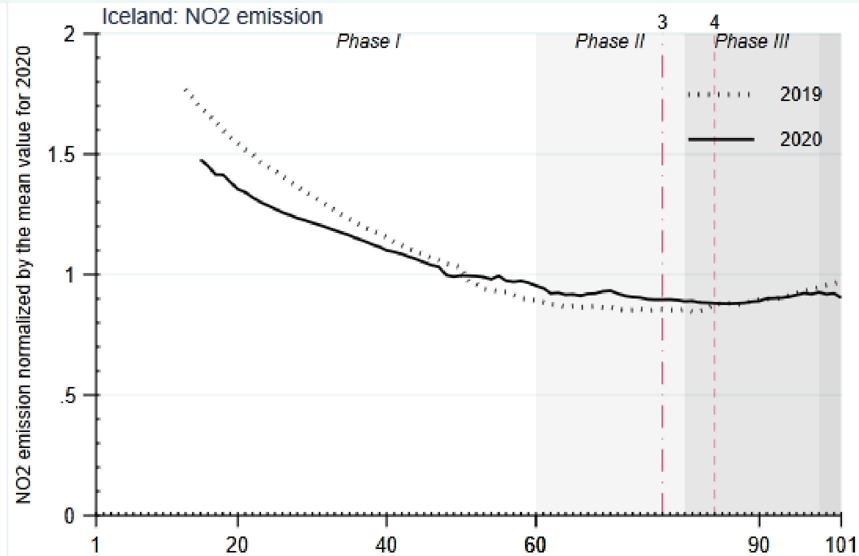

Greece: Electricity
Phase I
Phase II
Phase III
Phase IV
3,4
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 23
2. Partial lockdown: None
3. School lockdown: Mar 11
4. Events lockdown: Mar 09
1.6
1.4
1.2
1
.8
.6
1
20
40
60
83
90
100
108
Greece: NO2 emission
Phase I
Phase II
Phase III
IV
3,4
1
2019
2020
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
1
20
40
60
83
90
101
Greece: Mobility
Phase I
Phase II
Phase III
Phase IV
3,4
1
Driving
Walking
Mobility relative to Jan 13, 2020
2
1.5
1
.5
0
13
20
40
60
83
90
100
112
Day of the year

Hungary

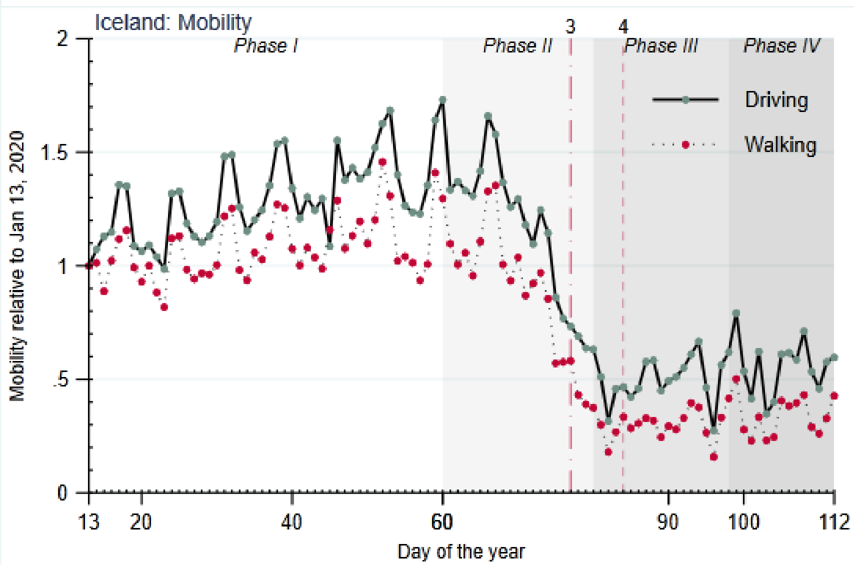


Hungary: Electricity
Phase I
Phase II
Phase III
3,4
2
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 28
2. Partial lockdown: Mar 16
3. School lockdown: Mar 11
4. Events lockdown: Mar 11
Hungary: NO2 emission
NO2 emission normalized by the mean value for 2020
Hungary: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Hungary: *Budapest* : NO2 emission
Day of the year

Iceland

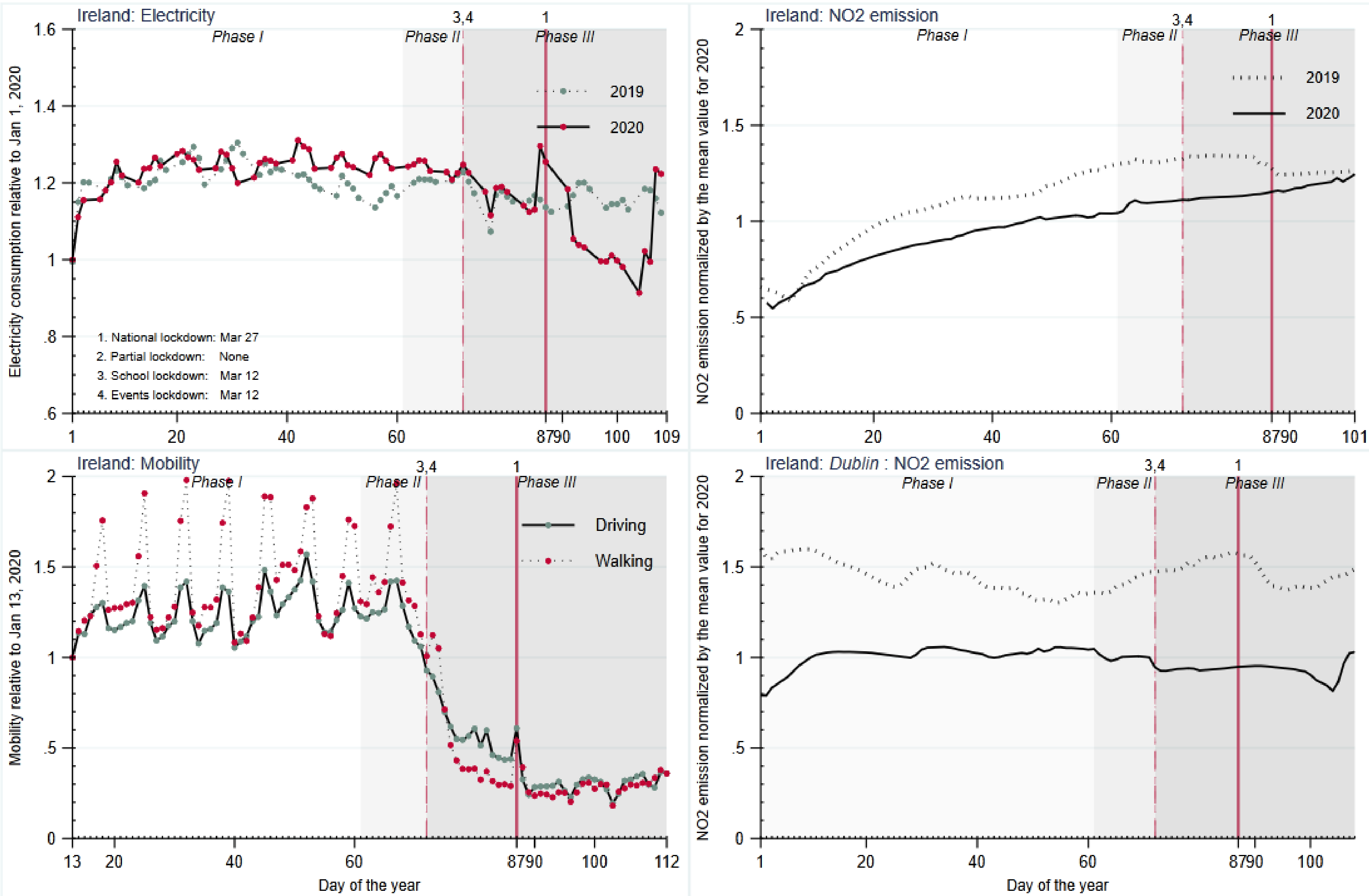


Iceland: NO2 emission
NO2 emission normalized by the mean value for 2020
Phase I
Phase II
Phase III
3
4
2019
2020
2
1.5
1
.5
0
1
20
40
60
90
101



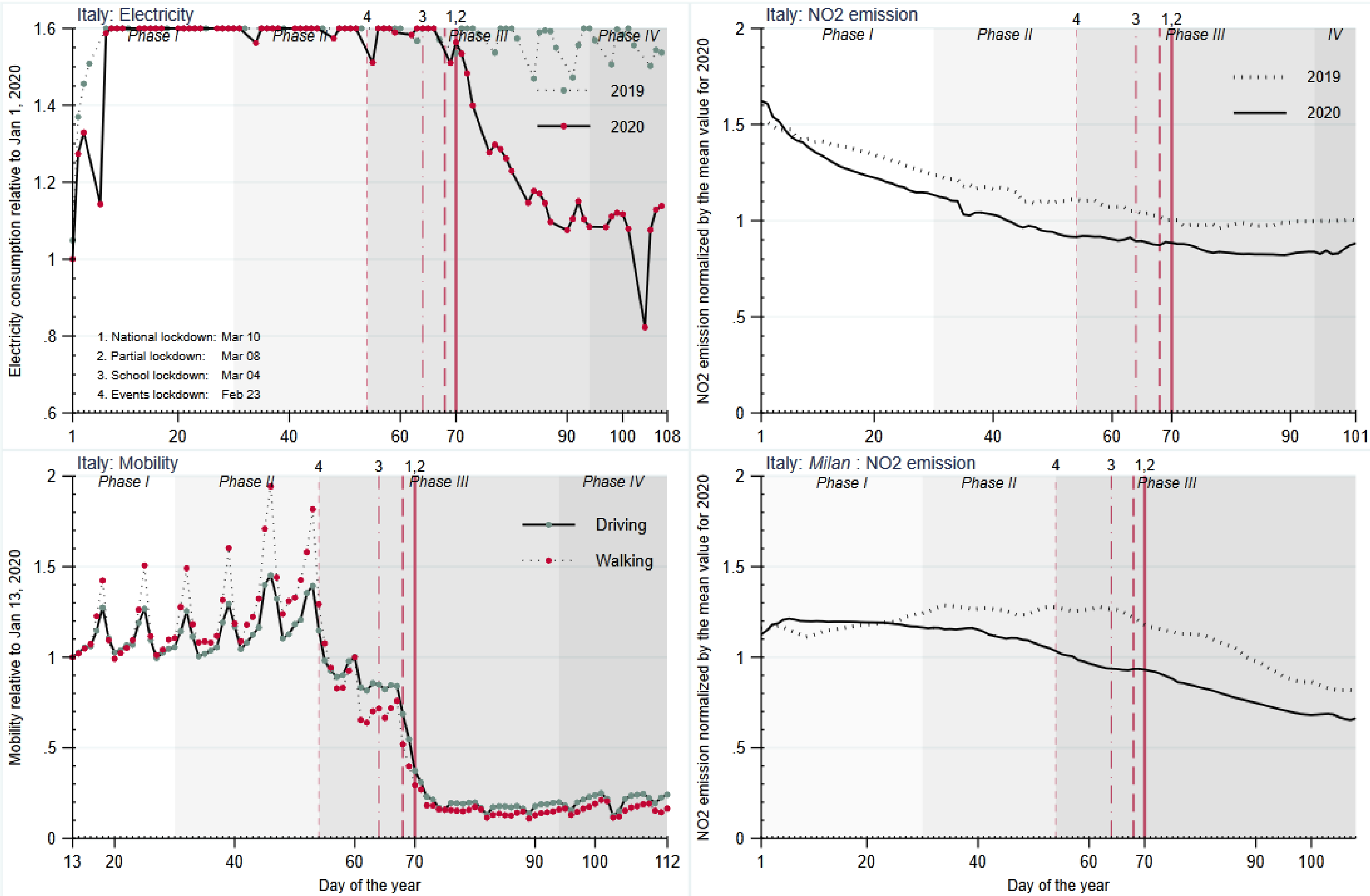
Iceland: Mobility
Mobility relative to Jan 13, 2020
Phase I
Phase II
Phase III
Phase IV
3
4
Driving
Walking
2
1.5
1
.5
0
13
20
40
60
90
100
112
Day of the year

Ireland



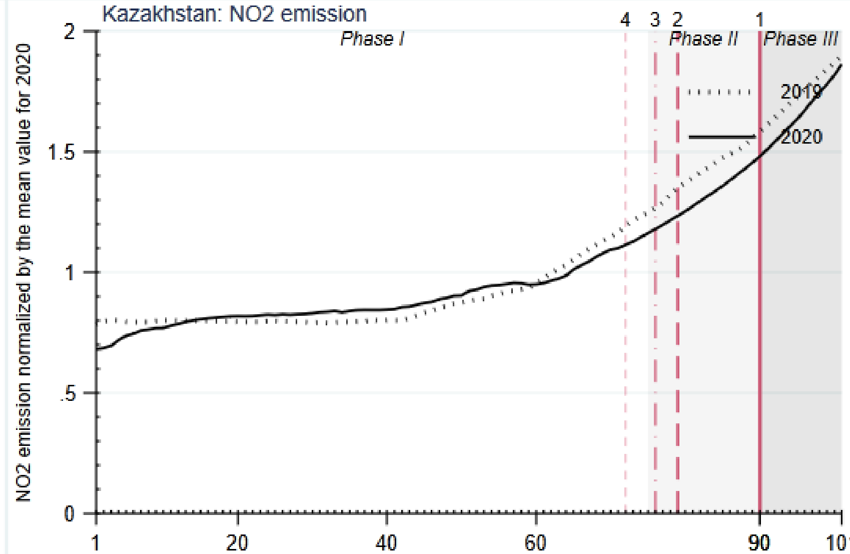
Ireland: Electricity
Phase I
Phase II
Phase III
3,4
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1.6
1.4
1.2
1
.8
.6
1. National lockdown: Mar 27
2. Partial lockdown: None
3. School lockdown: Mar 12
4. Events lockdown: Mar 12
1
20
40
60
8790
100
109
Ireland: NO2 emission
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
101
Ireland: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
13
112
Day of the year
Ireland: Dublin : NO2 emission

Italy



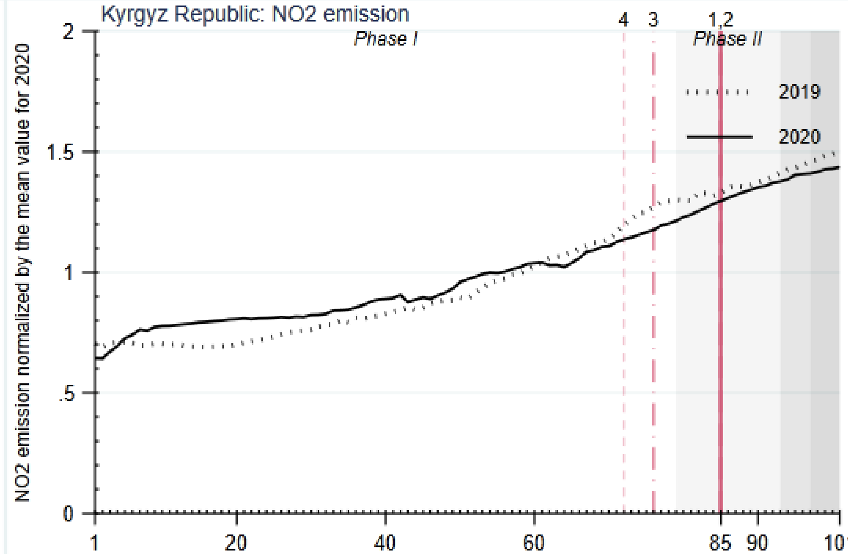
Italy: Electricity
Phase I
Phase II
Phase III
Phase IV
4
3
1,2
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 10
2. Partial lockdown: Mar 08
3. School lockdown: Mar 04
4. Events lockdown: Feb 23
Italy: NO2 emission
IV
NO2 emission normalized by the mean value for 2020
Italy: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Italy: *Milan* : NO2 emission

Kazakhstan

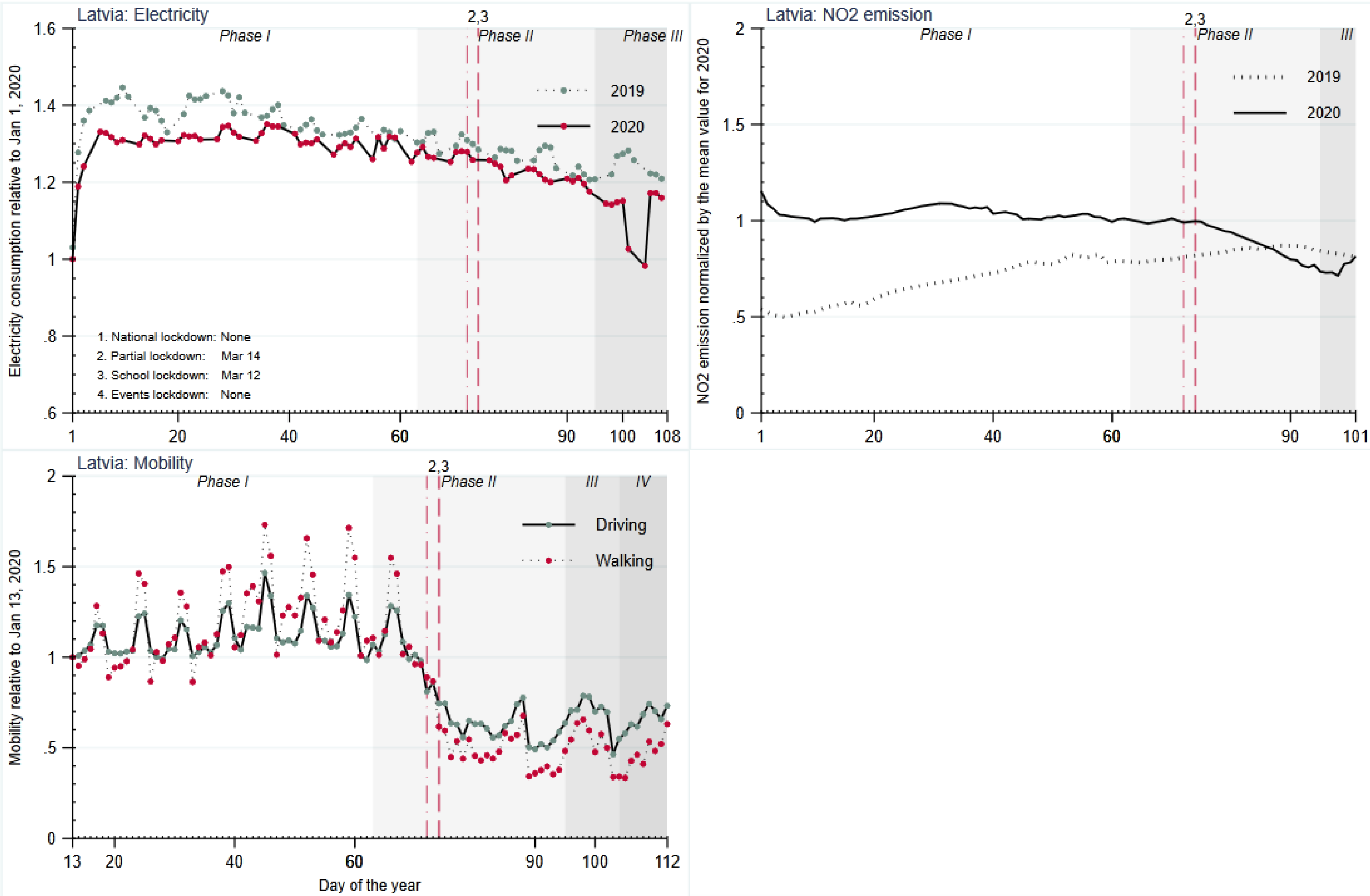


Kazakhstan: NO2 emission
4
3
2
1
Phase I
Phase II
Phase III
2019
2020
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
1
20
40
60
90
101

Kyrgyz Republic

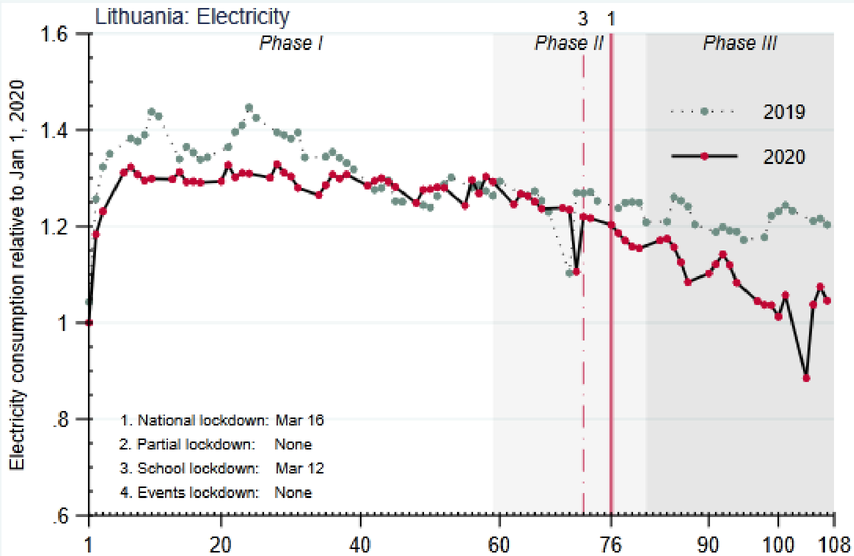


Latvia

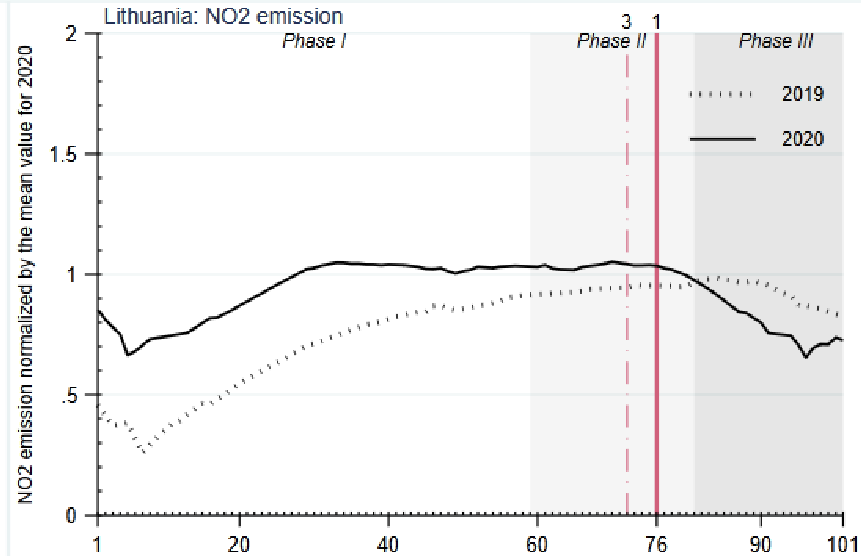


Latvia: Electricity
Phase I
Phase II
Phase III
2,3
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: None
2. Partial lockdown: Mar 14
3. School lockdown: Mar 12
4. Events lockdown: None
Latvia: NO2 emission
Phase I
Phase II
III
2,3
2019
2020
NO2 emission normalized by the mean value for 2020
Latvia: Mobility
Phase I
Phase II
III
IV
2,3
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year

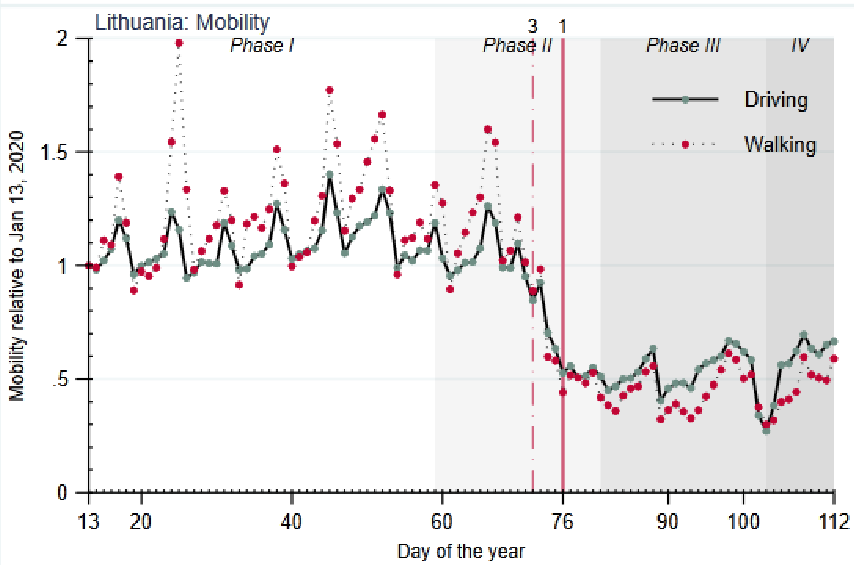
Lithuania



Lithuania: Electricity
Phase I
Phase II
Phase III
3
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 16
2. Partial lockdown: None
3. School lockdown: Mar 12
4. Events lockdown: None

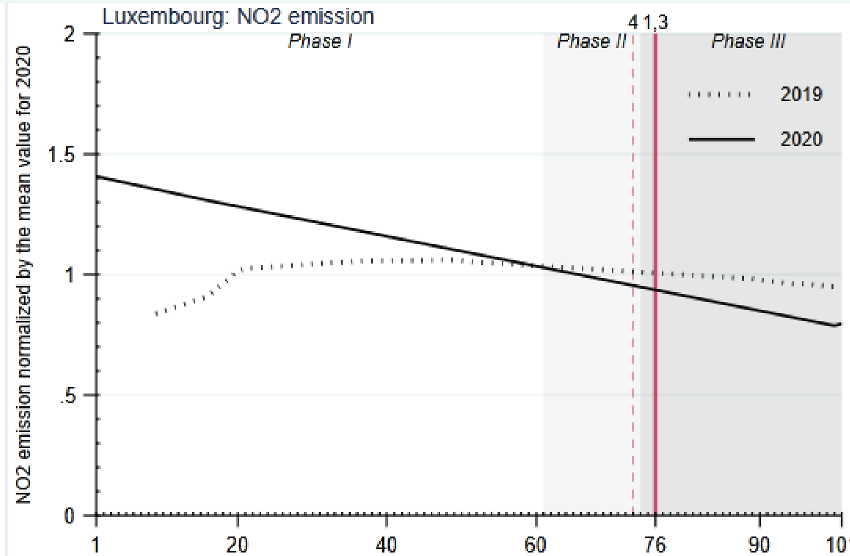


Lithuania: NO2 emission
Phase I
Phase II
Phase III
3
1
2019
2020
NO2 emission normalized by the mean value for 2020



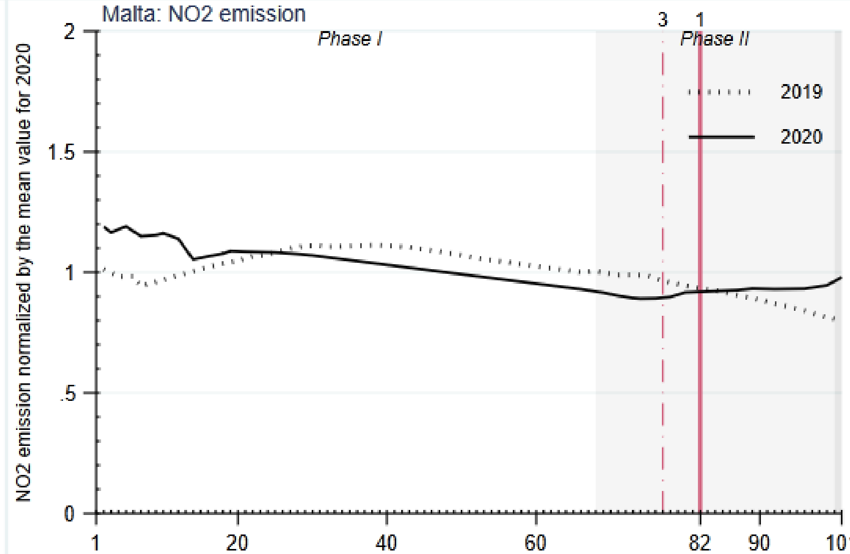
Lithuania: Mobility
Phase I
Phase II
Phase III
IV
3
1
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year

Luxembourg



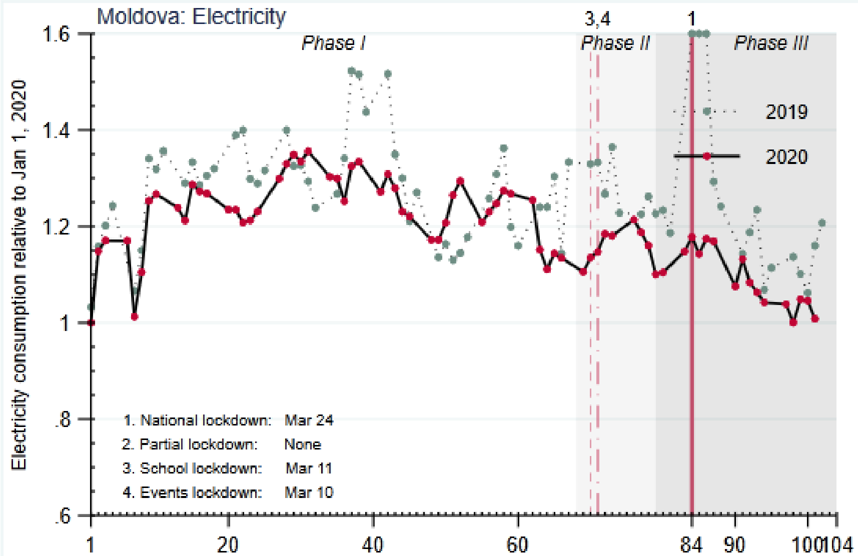
Luxembourg: NO2 emission
Phase I
Phase II
Phase III
4 1,3
2019
2020
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
1
20
40
60
76
90
101

Malta

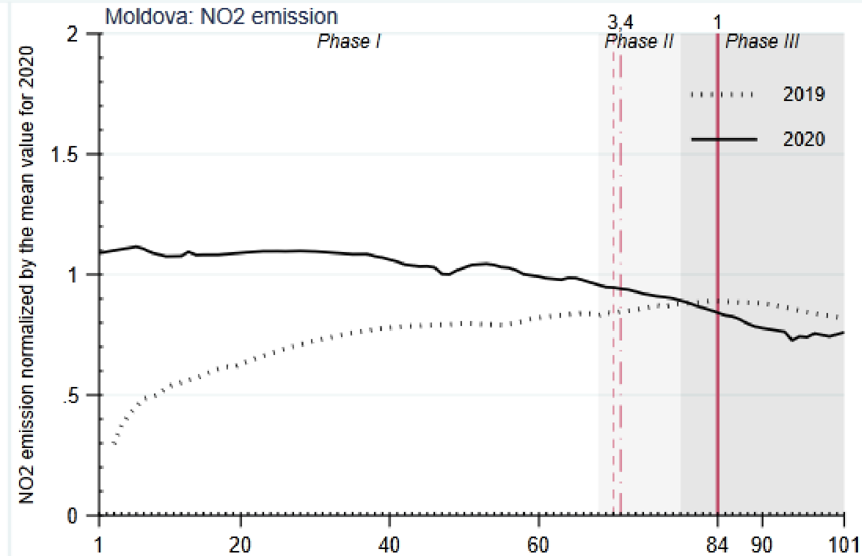


Malta: NO2 emission
Phase I
Phase II
3
1
2019
2020
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
1
20
40
60
82
90
101

Moldova

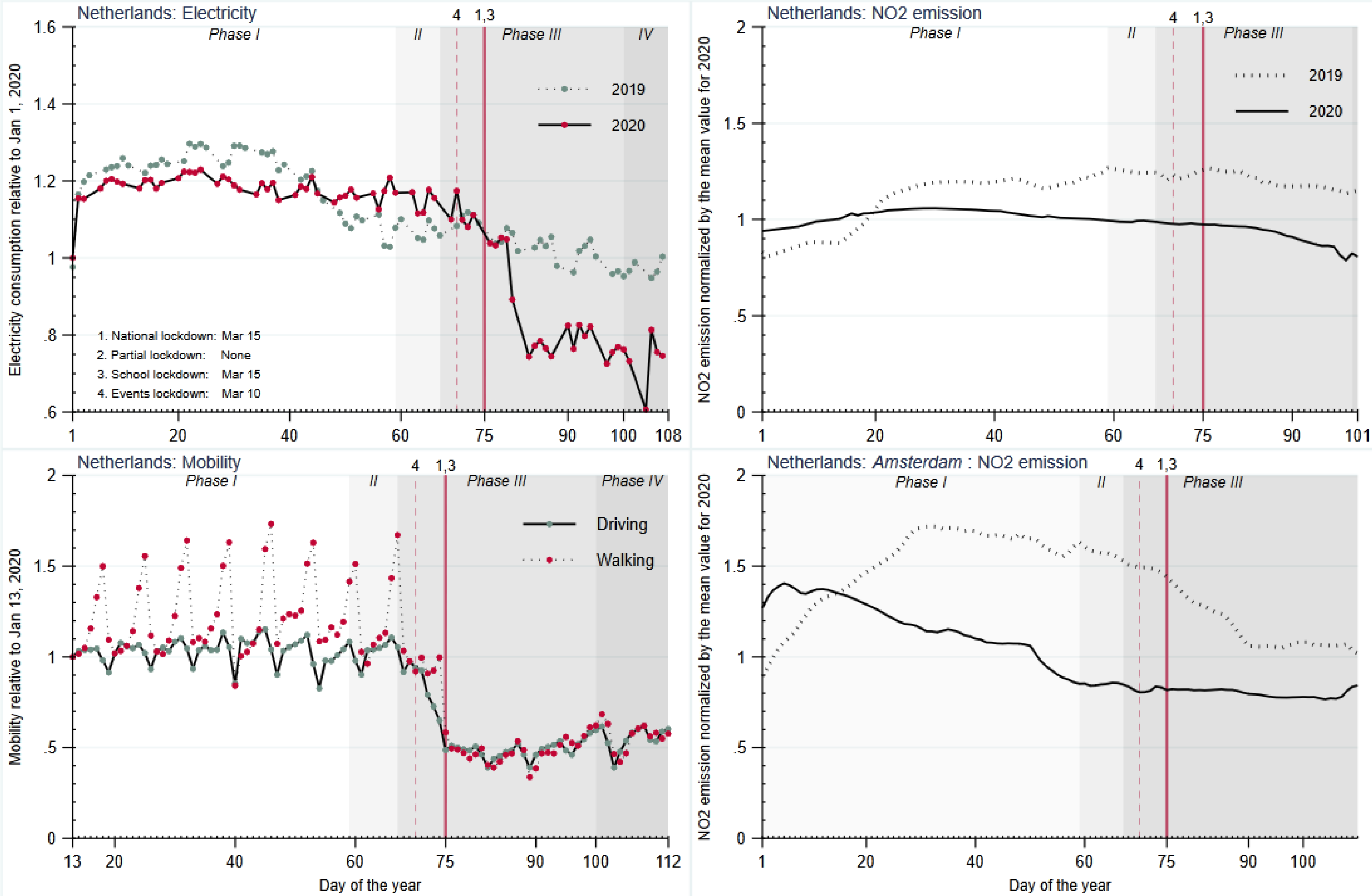


Moldova: Electricity
3,4
1
Phase I
Phase II
Phase III
2019
2020
Electricity consumption relative to Jan 1, 2020
1.6
1.4
1.2
1
.8
.6
1. National lockdown: Mar 24
2. Partial lockdown: None
3. School lockdown: Mar 11
4. Events lockdown: Mar 10
1
20
40
60
84
90
100
104

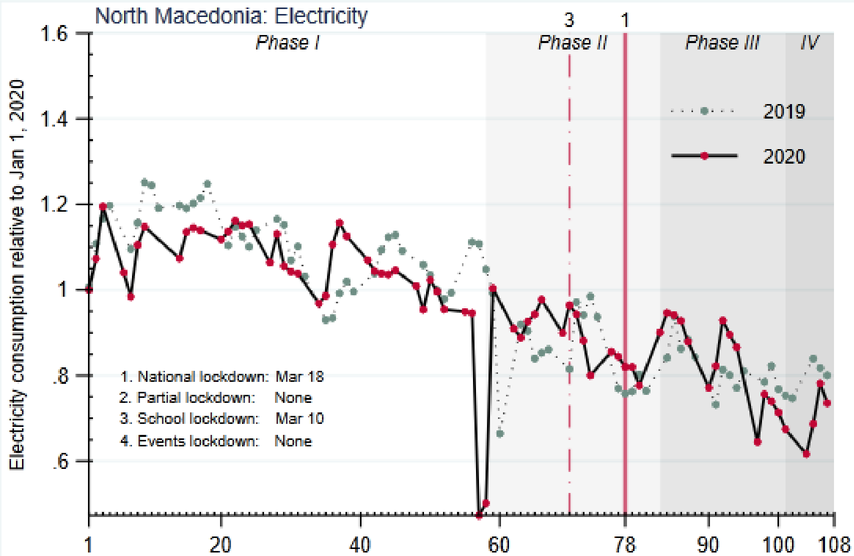


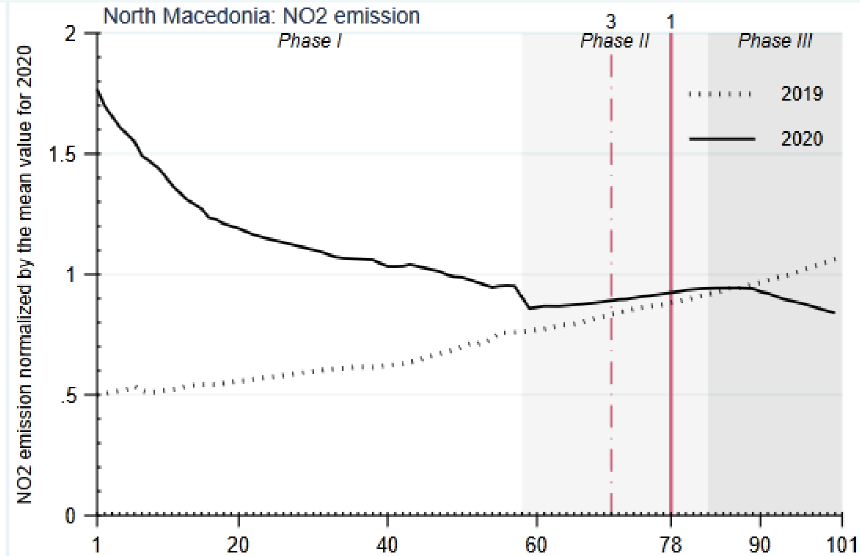
Moldova: NO2 emission
3,4
1
Phase I
Phase II
Phase III
2019
2020
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
1
20
40
60
84
90
101

Netherlands

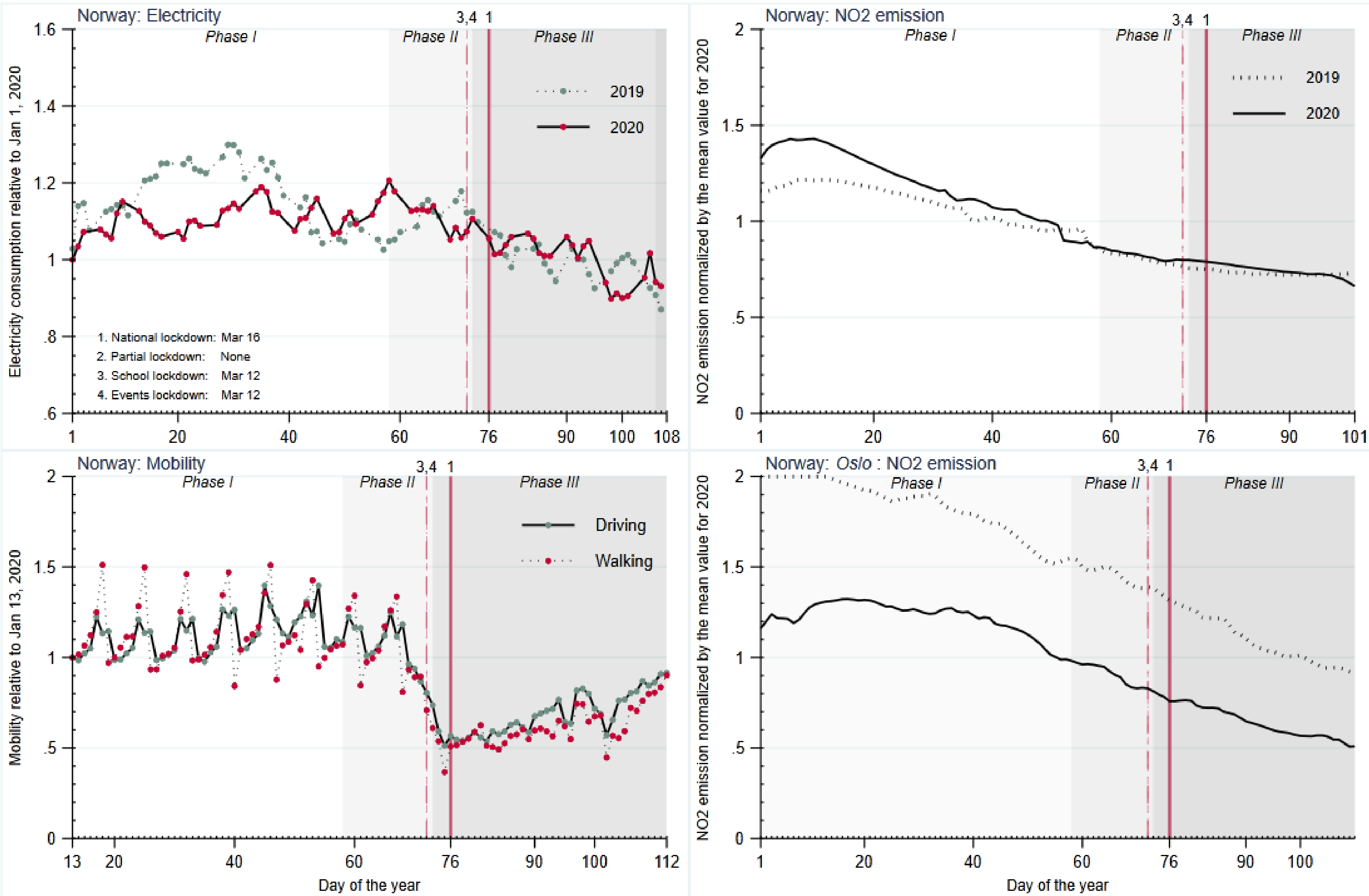


North Macedonia



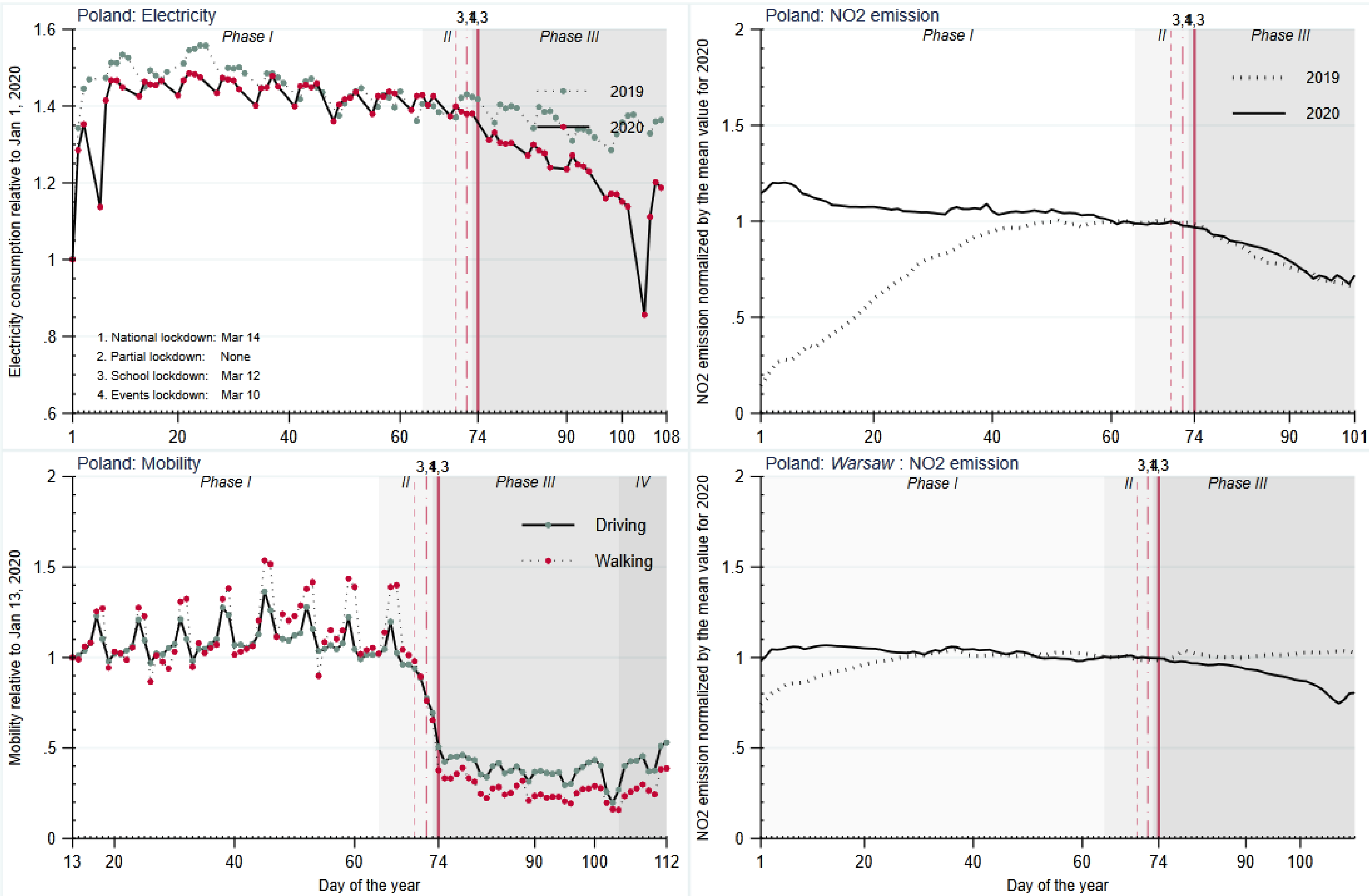


Norway

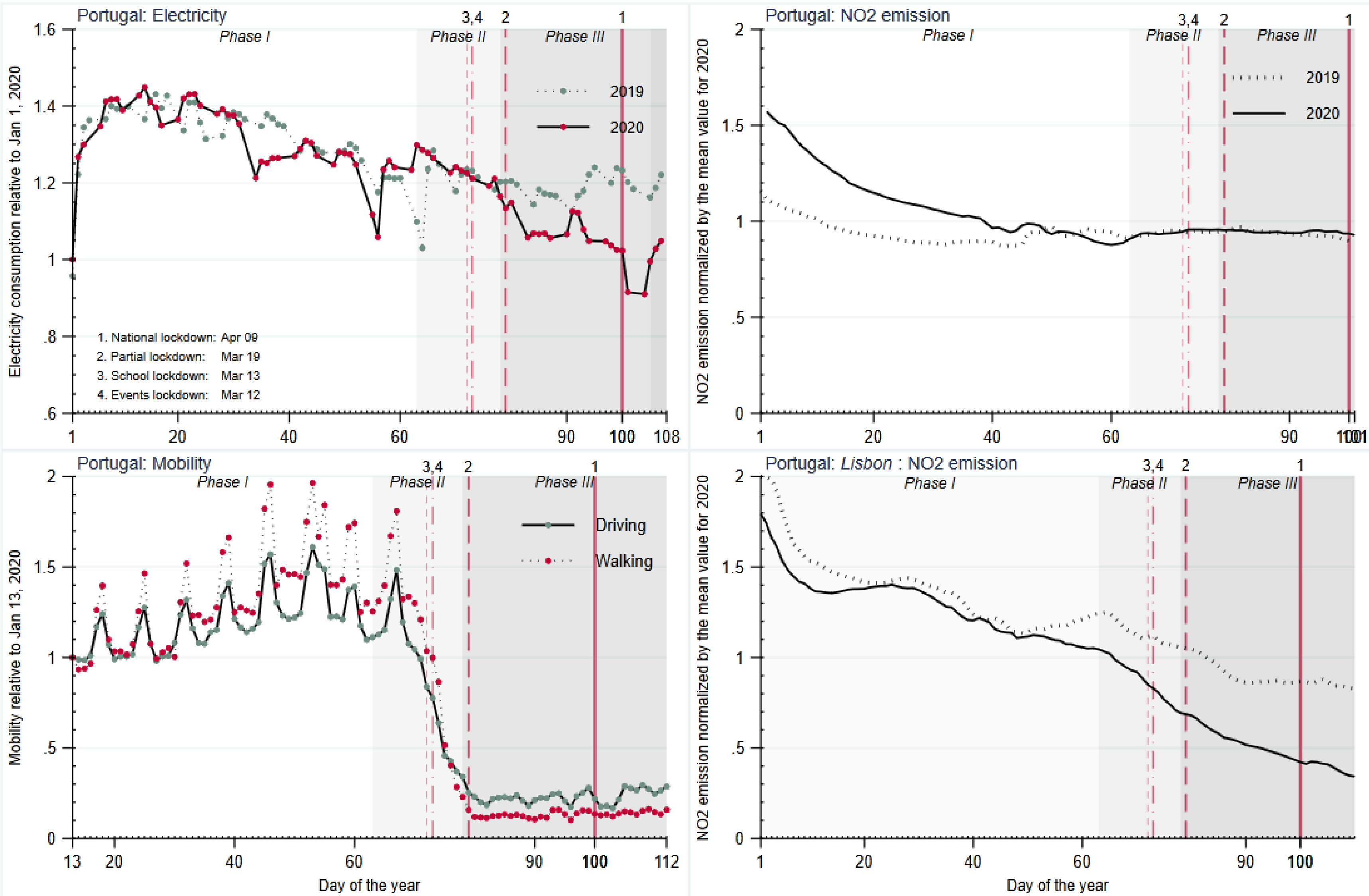


Norway: Electricity
Phase I
Phase II
Phase III
3,4 1
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 16
2. Partial lockdown: None
3. School lockdown: Mar 12
4. Events lockdown: Mar 12
Norway: NO2 emission
NO2 emission normalized by the mean value for 2020
Norway: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Norway: *Oslo* : NO2 emission

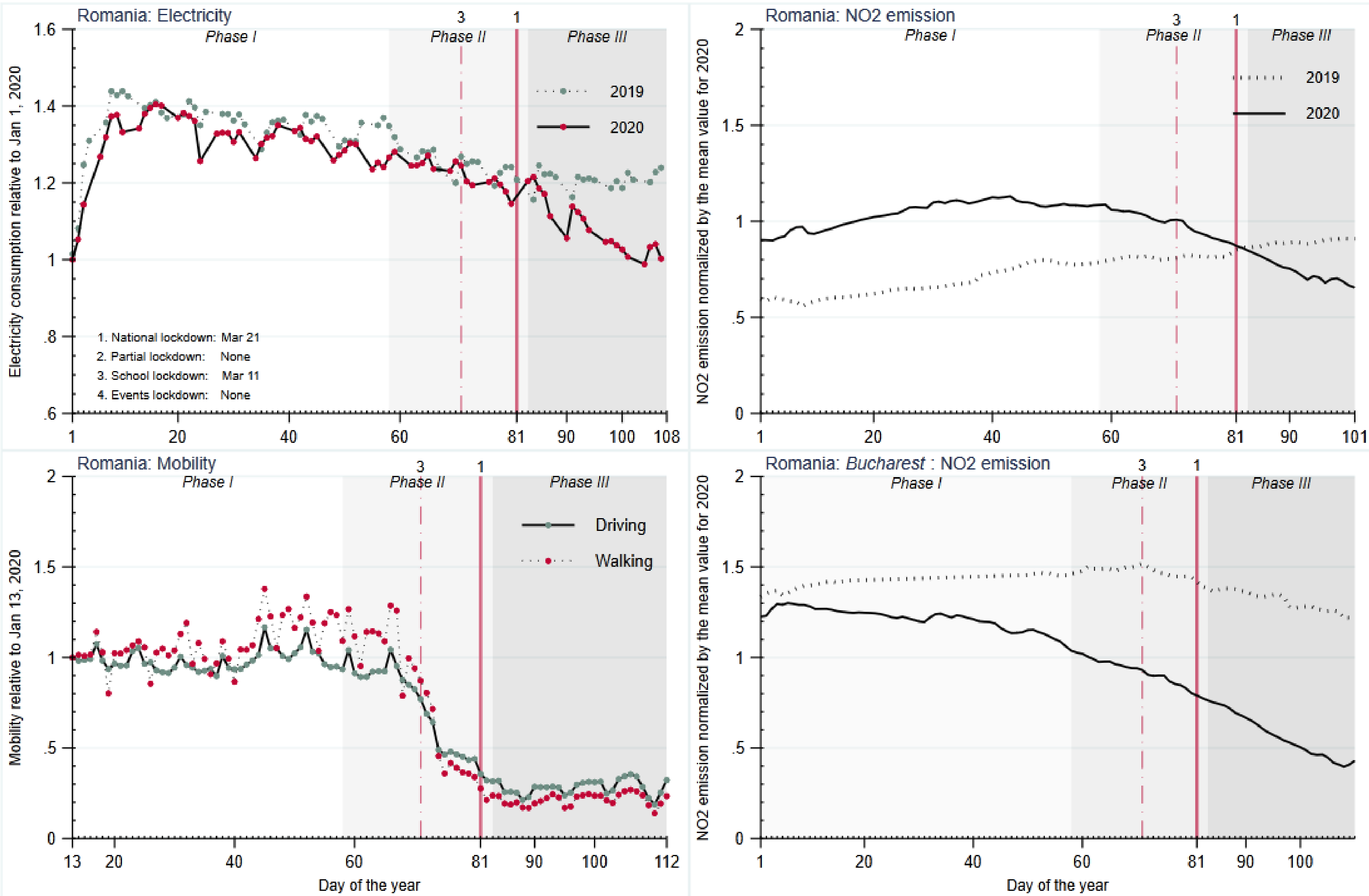
Poland


Poland: Electricity
Phase I
II
Phase III
3,4,3
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 14
2. Partial lockdown: None
3. School lockdown: Mar 12
4. Events lockdown: Mar 10
Poland: NO2 emission
NO2 emission normalized by the mean value for 2020
Poland: Mobility
IV
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Poland: Warsaw : NO2 emission

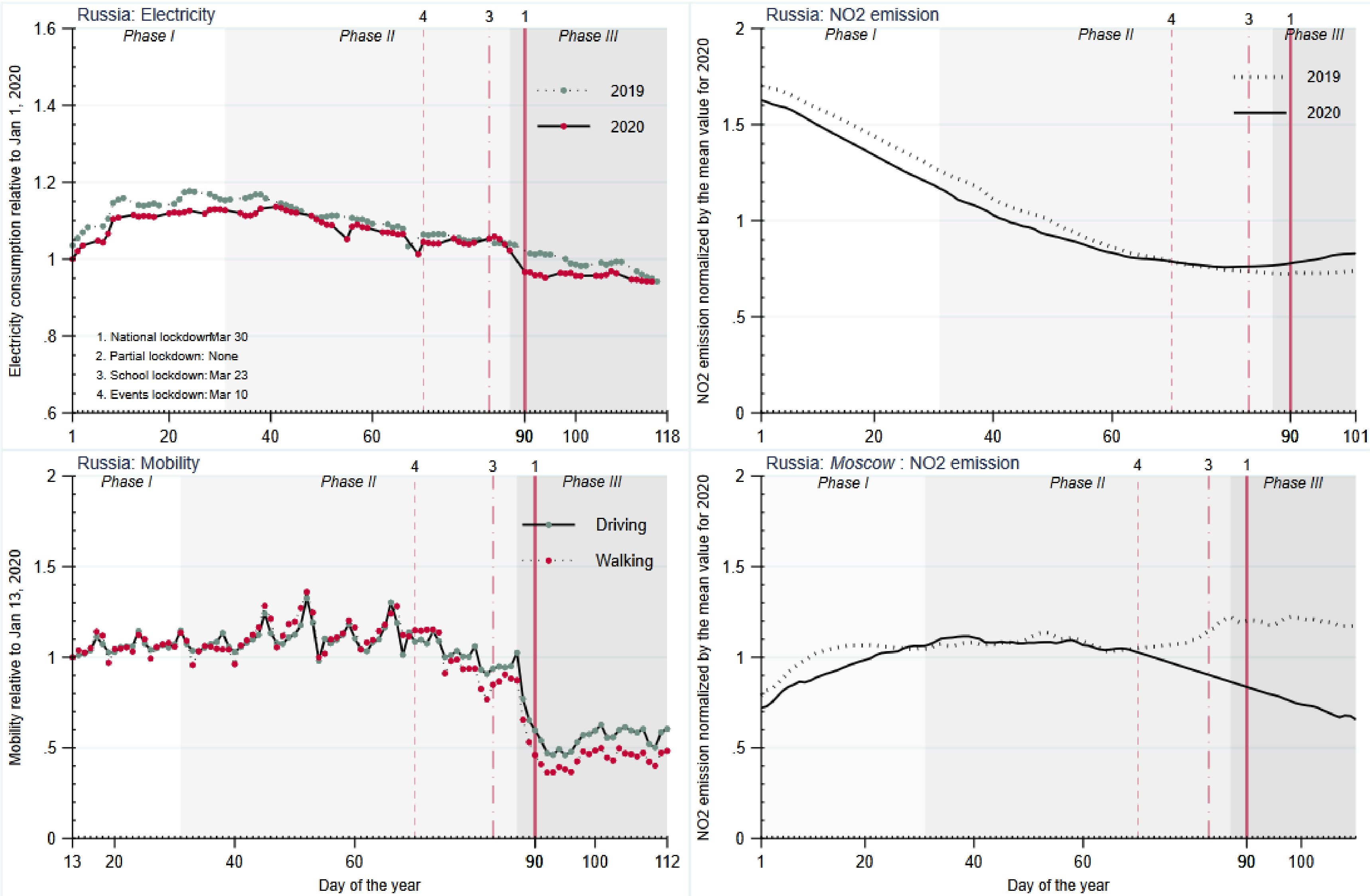
Portugal


Portugal: Electricity
Phase I
Phase II
Phase III
3,4
2
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Apr 09
2. Partial lockdown: Mar 19
3. School lockdown: Mar 13
4. Events lockdown: Mar 12
Portugal: NO2 emission
NO2 emission normalized by the mean value for 2020
Portugal: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Portugal: *Lisbon* : NO2 emission
NO2 emission normalized by the mean value for 2020
Day of the year

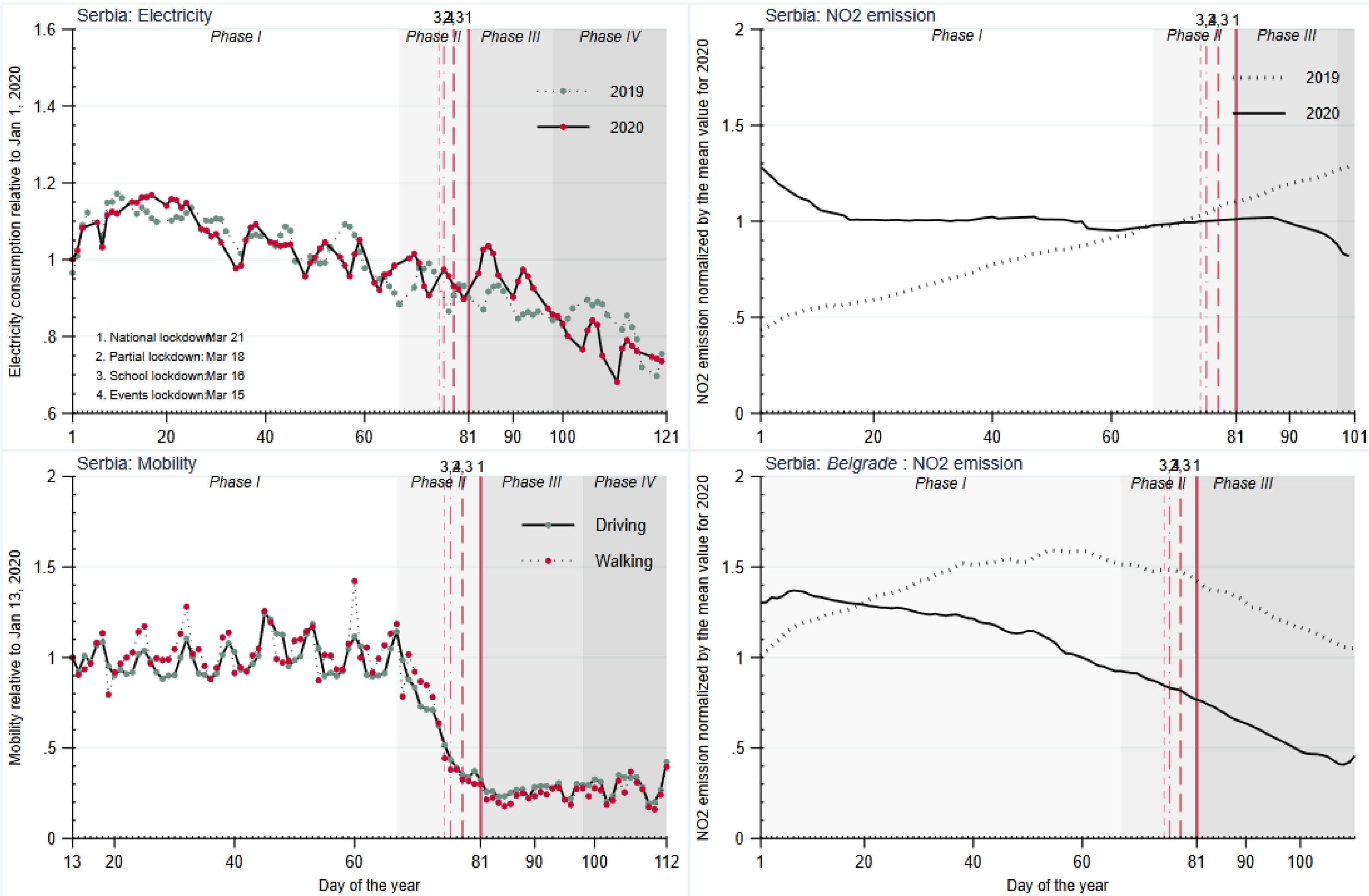
Romania


Romania: Electricity
Phase I
Phase II
Phase III
2019
2020
1. National lockdown: Mar 21
2. Partial lockdown: None
3. School lockdown: Mar 11
4. Events lockdown: None
Electricity consumption relative to Jan 1, 2020
Romania: NO2 emission
NO2 emission normalized by the mean value for 2020
Romania: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Romania: Bucharest : NO2 emission

Russia

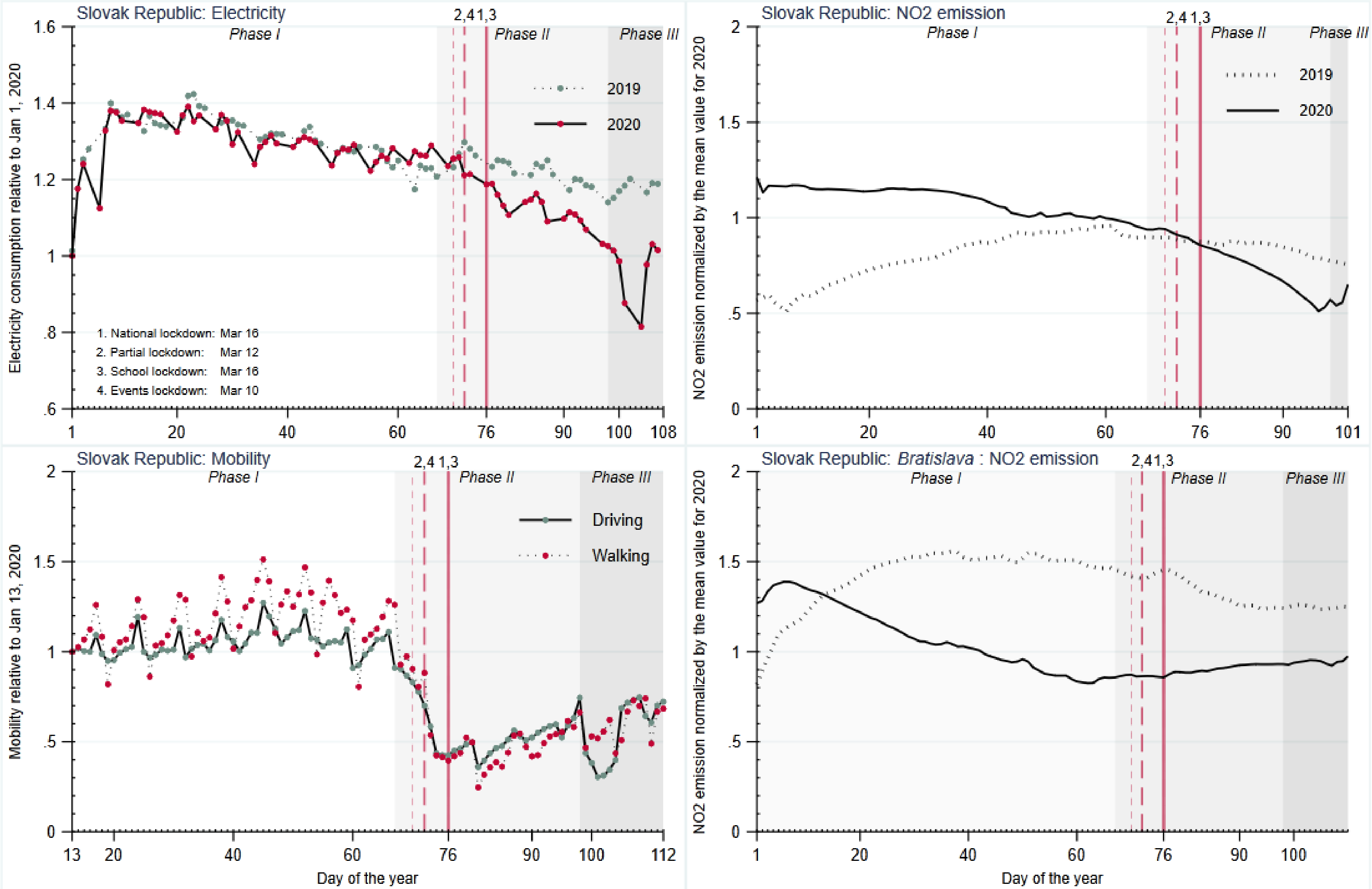

Russia: Electricity
Phase I
Phase II
Phase III
4
3
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1.6
1.4
1.2
1
.8
.6
1
20
40
60
90
100
118
1. National lockdownMar 30
2. Partial lockdown: None
3. School lockdown: Mar 23
4. Events lockdown: Mar 10
Russia: NO2 emission
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
101
Russia: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
13
112
Day of the year
Russia: Moscow : NO2 emission

Serbia

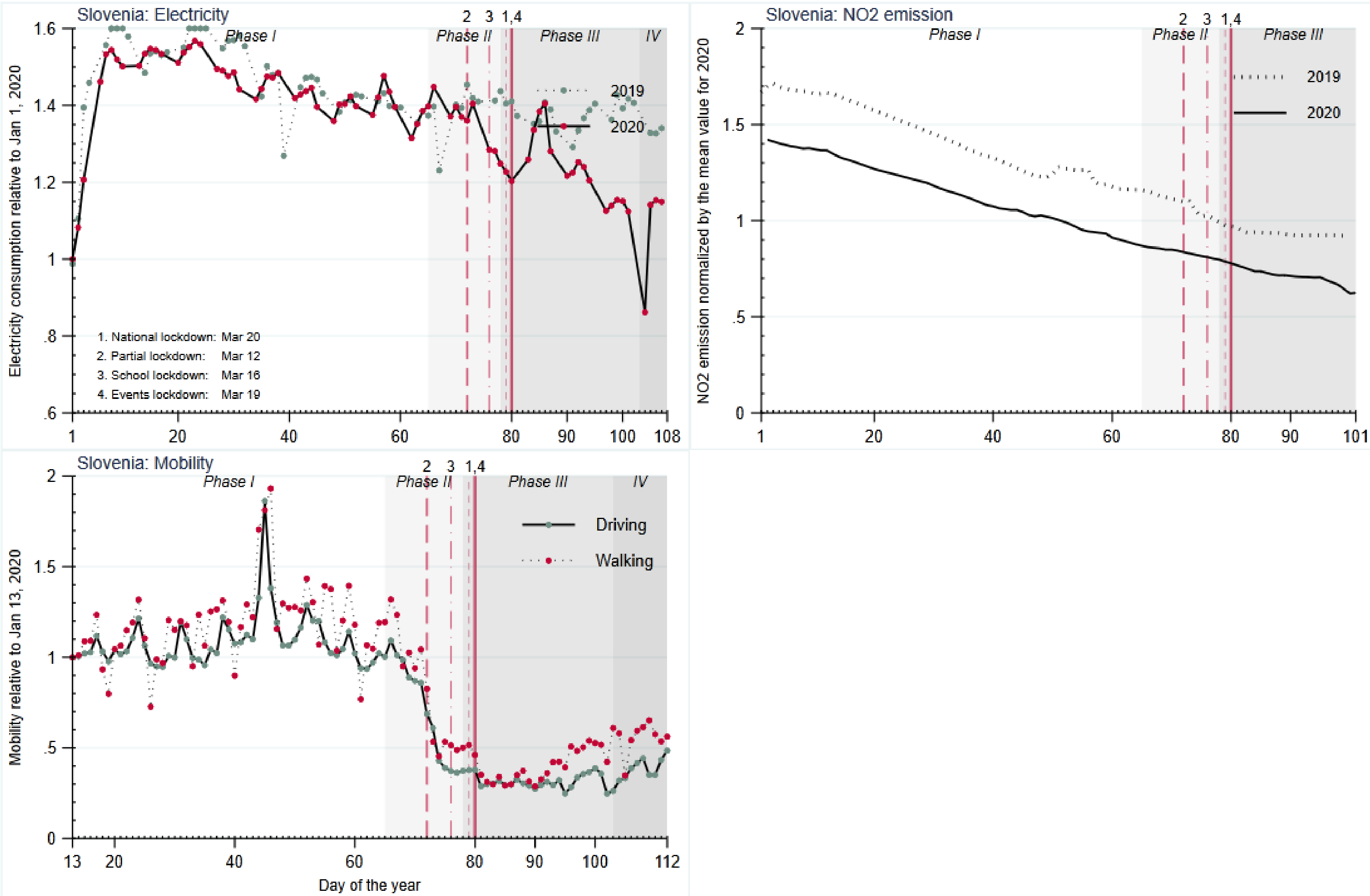


Serbia: Electricity
Phase I
Phase II
Phase III
Phase IV
2019
2020
1. National lockdown:Mar 21
2. Partial lockdown: Mar 18
3. School lockdown:Mar 16
4. Events lockdown:Mar 15
Electricity consumption relative to Jan 1, 2020
Serbia: NO2 emission
NO2 emission normalized by the mean value for 2020
Serbia: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Serbia: *Belgrade* : NO2 emission

Slovak Republic

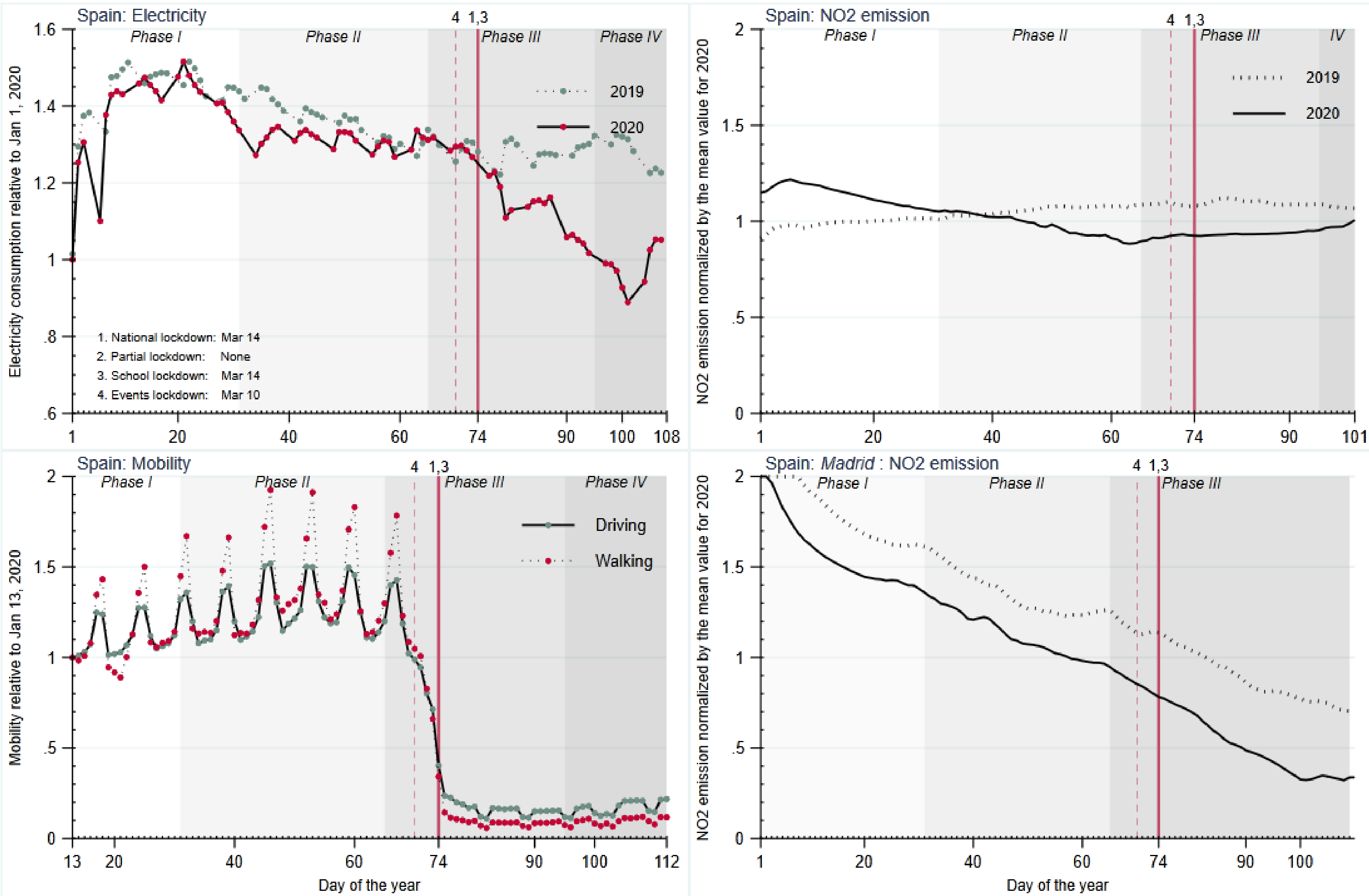


Slovenia



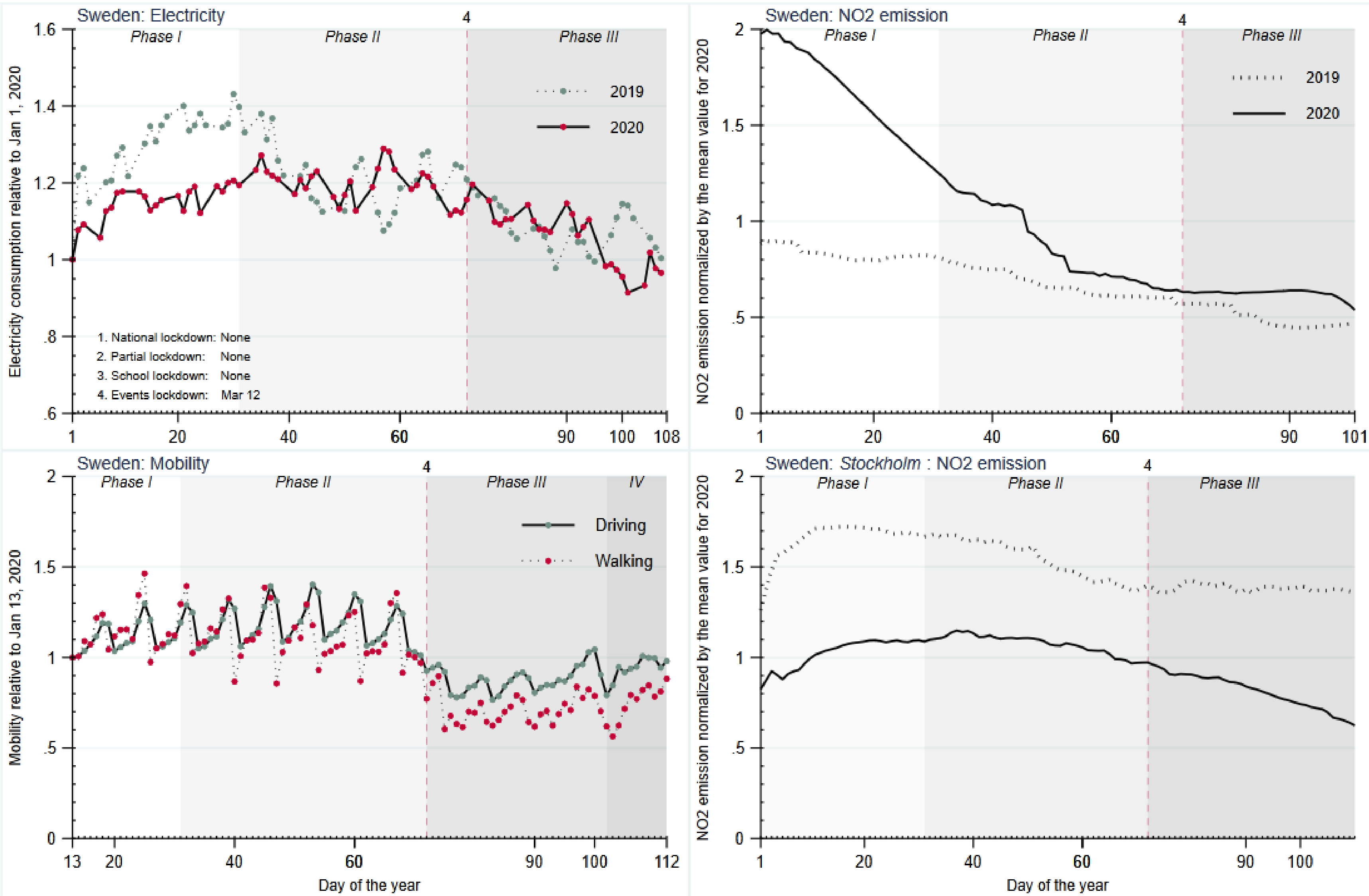
Slovenia: Electricity
Phase I
Phase II
Phase III
IV
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: Mar 20
2. Partial lockdown: Mar 12
3. School lockdown: Mar 16
4. Events lockdown: Mar 19
Slovenia: NO2 emission
NO2 emission normalized by the mean value for 2020
Slovenia: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year

Spain

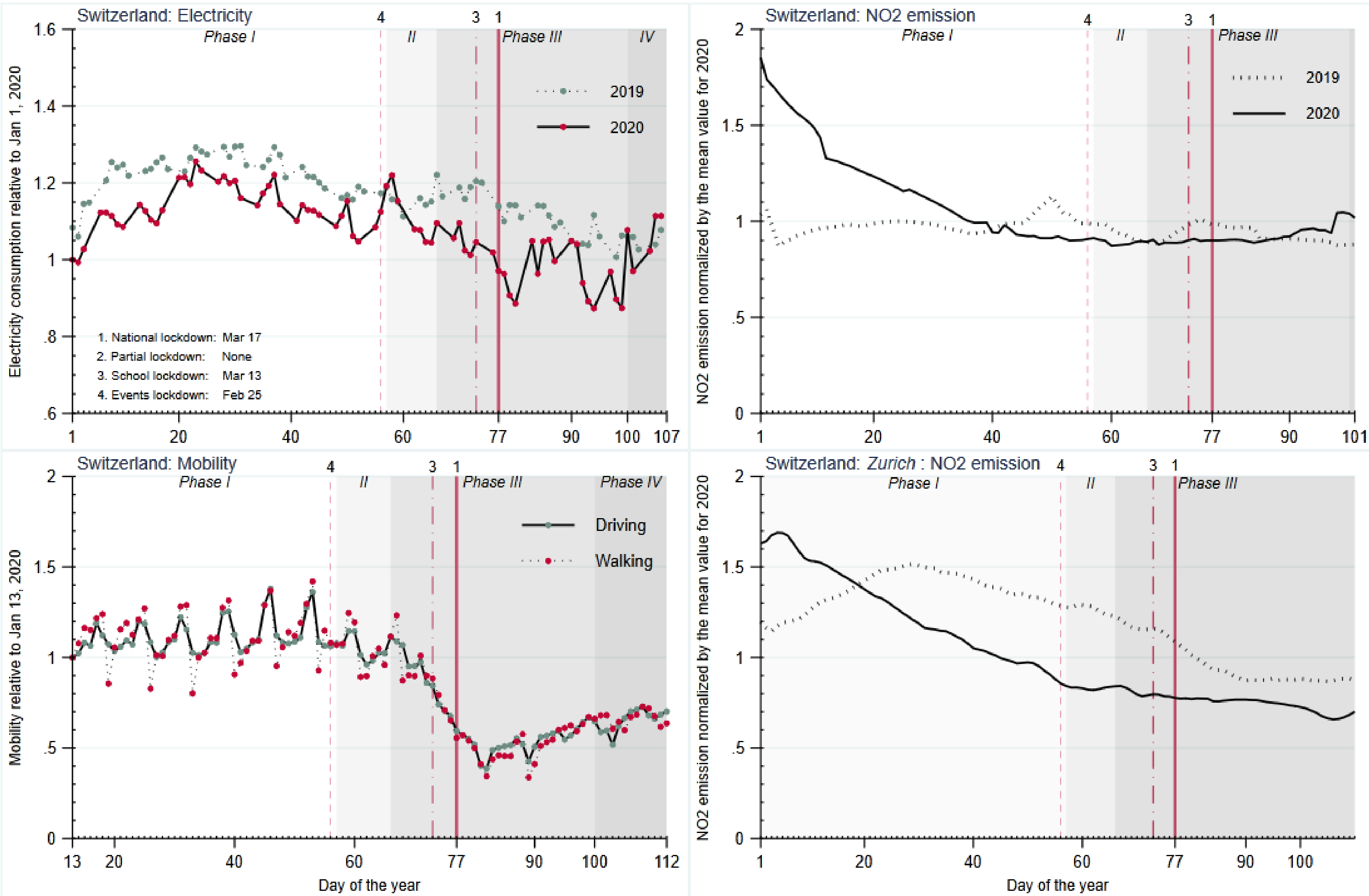


Spain: Electricity
Electricity consumption relative to Jan 1, 2020
Phase I
Phase II
Phase III
Phase IV
4
1,3
2019
2020
1. National lockdown: Mar 14
2. Partial lockdown: None
3. School lockdown: Mar 14
4. Events lockdown: Mar 10
Spain: NO2 emission
NO2 emission normalized by the mean value for 2020
IV
Spain: Mobility
Mobility relative to Jan 13, 2020
Driving
Walking
Day of the year
Spain: *Madrid* : NO2 emission

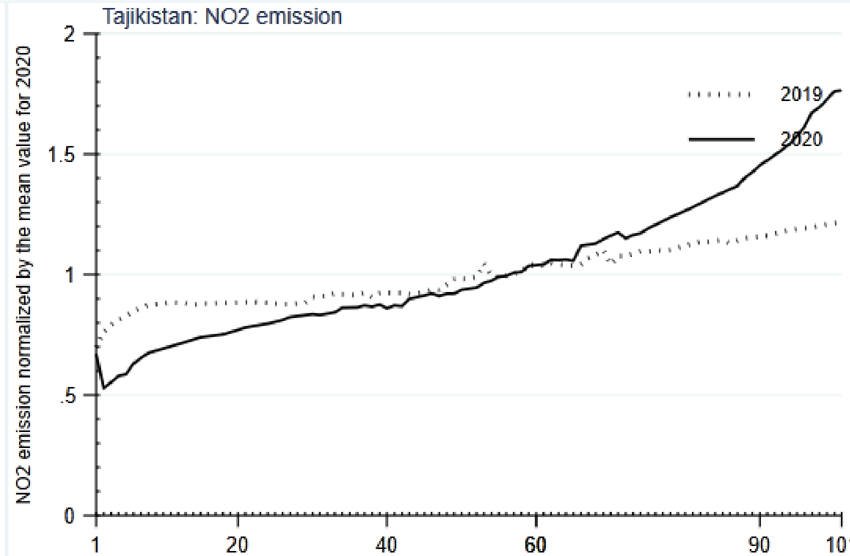
Sweden


Sweden: Electricity
Phase I
Phase II
Phase III
4
2019
2020
Electricity consumption relative to Jan 1, 2020
1. National lockdown: None
2. Partial lockdown: None
3. School lockdown: None
4. Events lockdown: Mar 12
Sweden: NO2 emission
NO2 emission normalized by the mean value for 2020
Sweden: Mobility
IV
Driving
Walking
Mobility relative to Jan 13, 2020
Sweden: Stockholm : NO2 emission
Day of the year

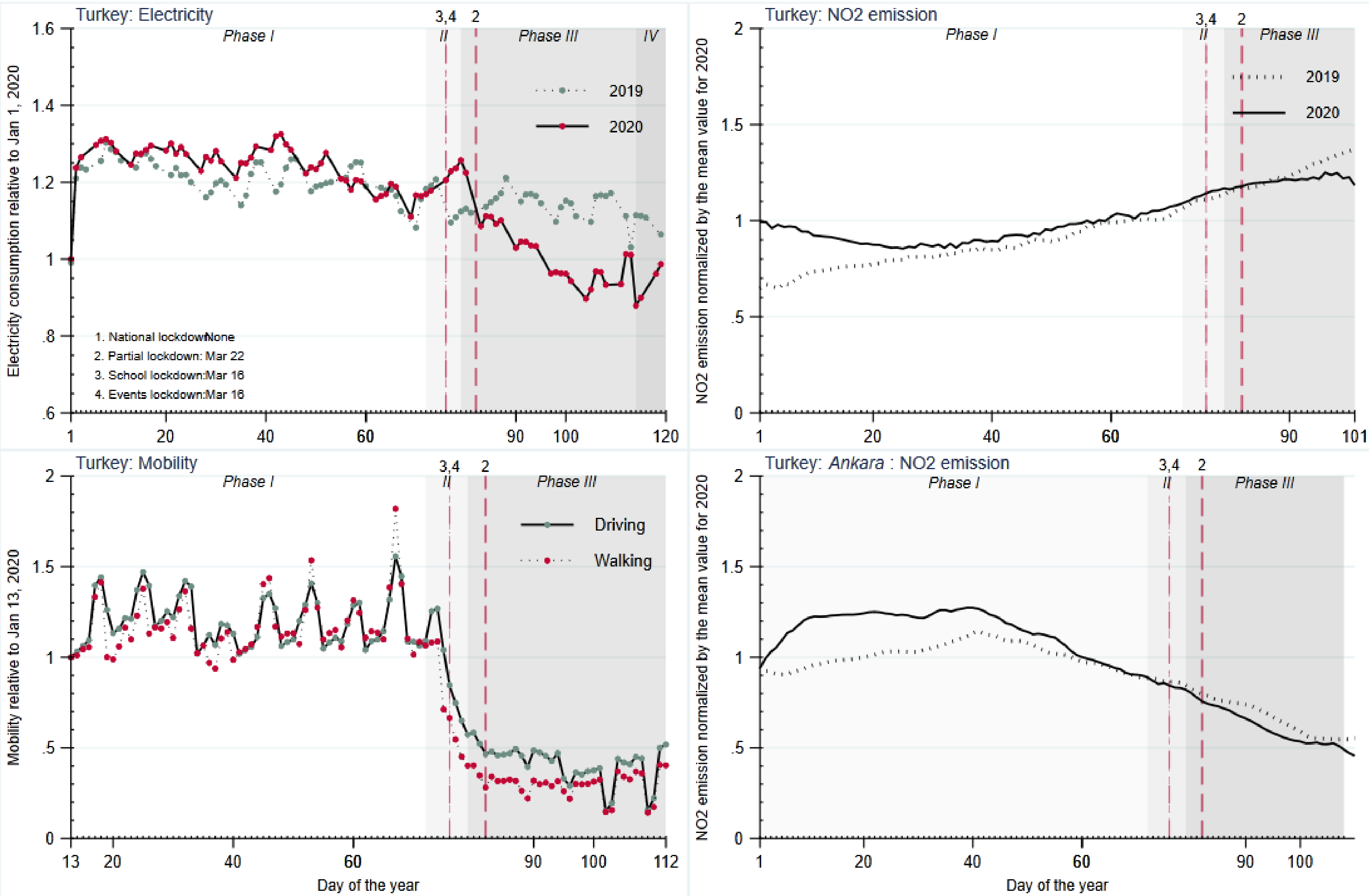
Switzerland



Tajikistan

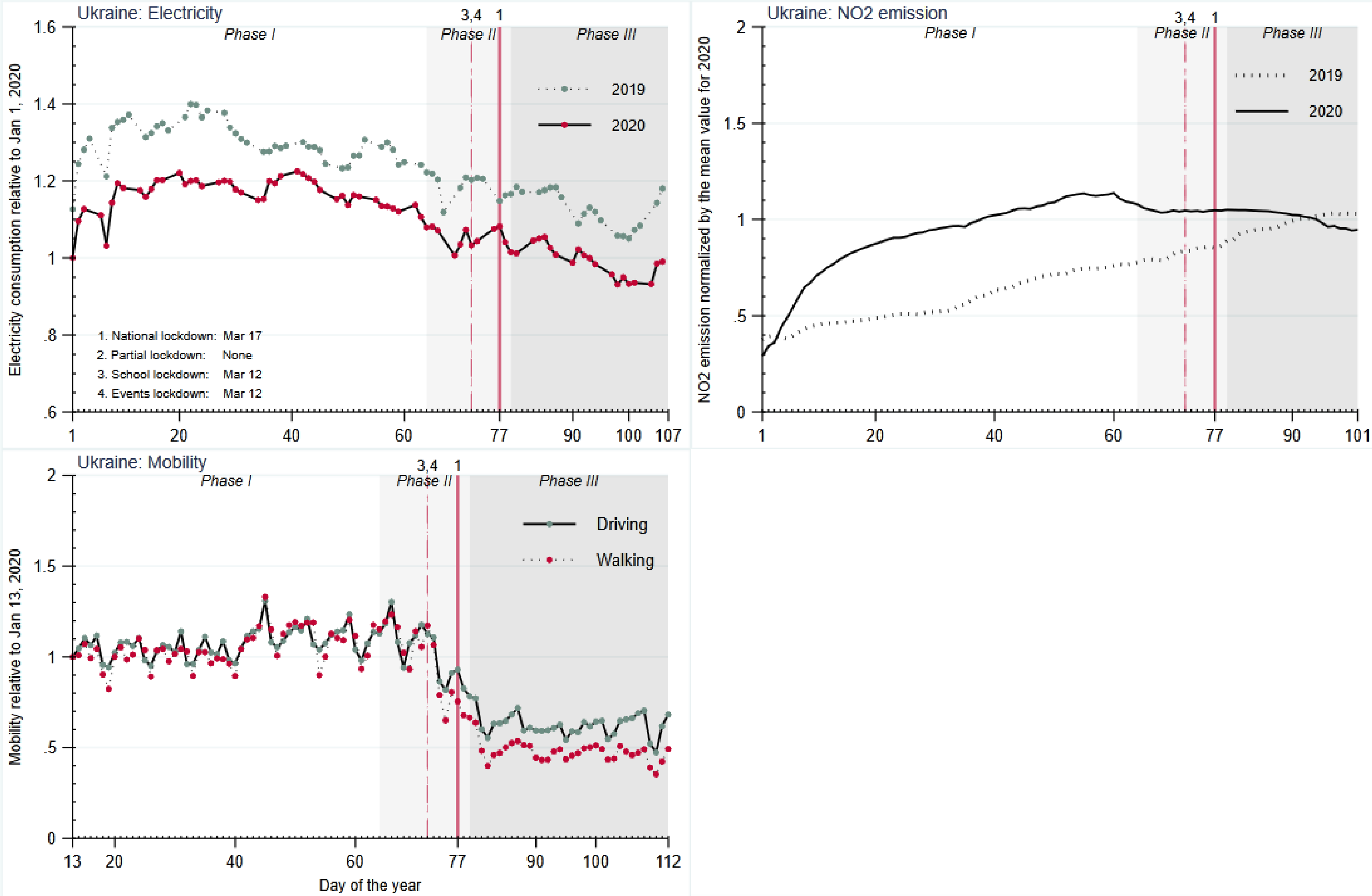

Tajikistan: NO2 emission
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
1
20
40
60
90
101
2019
2020

Turkey

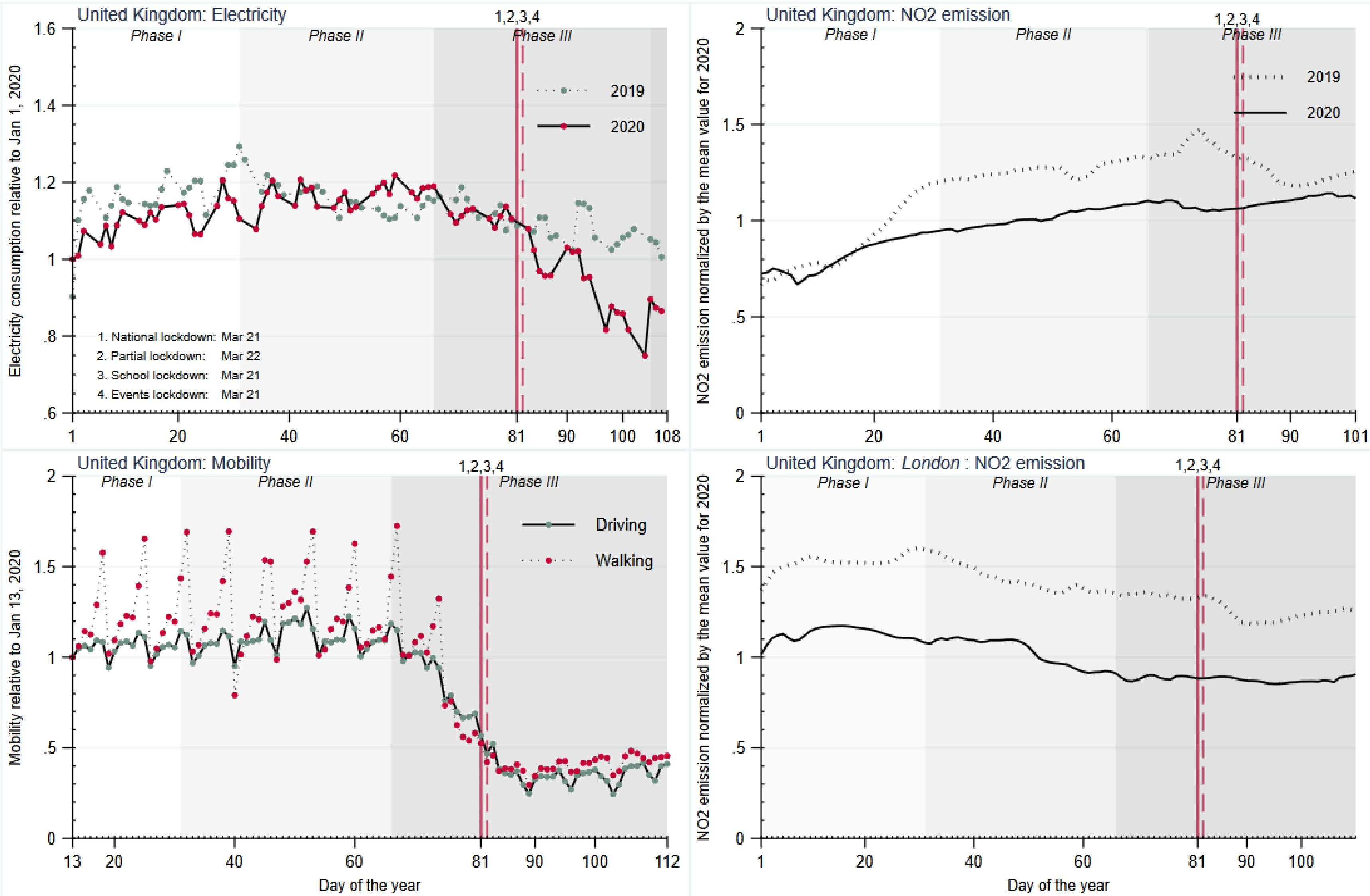


Turkey: Electricity
Phase I
3,4
II
2
Phase III
IV
2019
2020
1. National lockdown:None
2. Partial lockdown: Mar 22
3. School lockdown:Mar 16
4. Events lockdown:Mar 16
Electricity consumption relative to Jan 1, 2020
Turkey: NO2 emission
NO2 emission normalized by the mean value for 2020
Turkey: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
Day of the year
Turkey: Ankara : NO2 emission

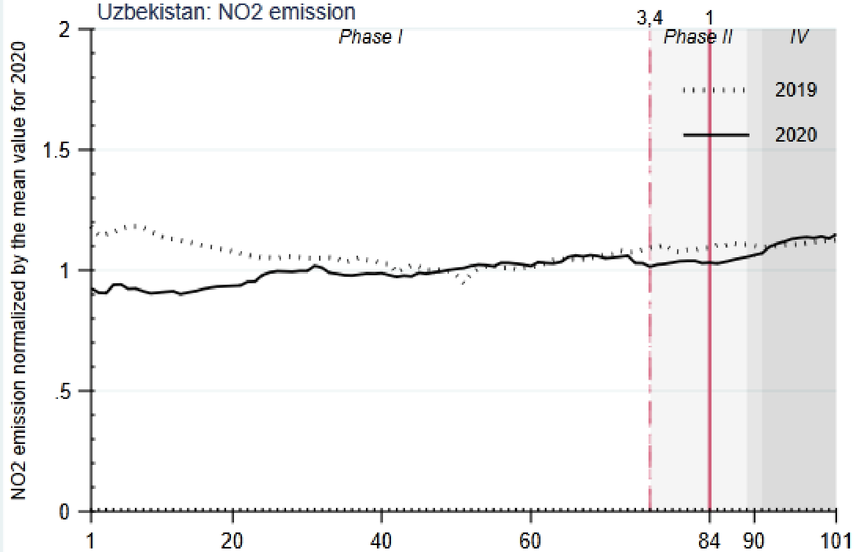
Ukraine


Ukraine: Electricity
Phase I
Phase II
Phase III
3,4
1
2019
2020
Electricity consumption relative to Jan 1, 2020
1.6
1.4
1.2
1
.8
.6
1. National lockdown: Mar 17
2. Partial lockdown: None
3. School lockdown: Mar 12
4. Events lockdown: Mar 12
1
20
40
60
77
90
100
107
Ukraine: NO2 emission
NO2 emission normalized by the mean value for 2020
2
1.5
1
.5
0
101
Ukraine: Mobility
Driving
Walking
Mobility relative to Jan 13, 2020
13
112
Day of the year

United Kingdom



Uzbekistan



Uzbekistan: NO2 emission
NO2 emission normalized by the mean value for 2020
Phase I
Phase II
IV
3,4
1
2019
2020
2
1.5
1
.5
0
1
20
40
60
84
90
101