Decreases in global CO2 emissions due to COVID-19 pandemic

Zhu Liu[1*], Zhu Deng[1], Philippe Ciais[2], Ruixue Lei[3], Sha Feng[3], Steven J. Davis[4], Yuan Wang[5,6], Xu Yue[7], Yadong Lei[8] , Hao Zhou[8], Zhaonan Cai[9], Bo Zheng[2], Xinyu Dou[1], Duo Cui[1], Pan He[1], Biqing Zhu[1], Piyu Ke[1], Taochun Sun[1], Yuhui Wu[10], Runtao Guo[11], Tingxuan Han[12], Jinjun Xue[13, 14, 15], Qiang Zhang[1], Dabo Guan[1], Peng Gong[1], Daniel M. Kammen[16], Hans Joachim Schellnhuber[17]

[1] Department of Earth System Science, Tsinghua University, Beijing 100084, China.
[2] Laboratoire des Sciences du Climate et de l'Environnement LSCE, Batiment 706, Pte 25, Orme de Merisiers 91191 Gif-sur-Yvette, France
[3] Department of Meteorology and Atmospheric Science, The Pennsylvania State University University Park, PA 16802
[4] Department of Earth System Science, University of California, Irvine, 3232 Croul Hall, Irvine, CA 92697-3100, USA
[5] Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA, USA
[6] Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA
[7]Jiangsu Key Laboratory of Atmospheric Environment Monitoring and Pollution Control, Collaborative Innovation Center of Atmospheric Environment and Equipment Technology, School of Environmental Science and Engineering, Nanjing University of Information Science & Technology (NUIST), Nanjing 210044, China
[8] Climate Change Research Center, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China
[9]Key Laboratory of Middle Atmosphere and Global Environment Observation, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China.
[10]School of Environment School, Tsinghua University, Beijing 100084, China
[11] School of Environment School, Tsinghua University, Beijing 100084, China
[12] Department of Mathematical Sciences, Tsinghua University, Beijing 100084, China
[13] Center of Hubei Cooperative Innovation for Emissions Trading System, Wuhan, China
[14] Faculty of Management and Economics, Kunming University of Science and Technology, 13 Kunming, China
[15] Economic Research Centre of Nagoya University, Furo-cho, Chikusa-ku, Nagoya, Japan
[16] University of California, Berkeley, CA, USA
[17] Potsdam Institute for Climate Impact Research, 14412 Potsdam, Germany

Corresponding author: zhuliu@tsinghua.edu.cn

Abstract

Assessing the impacts of COVID-19 are of paramount importance for global sustainability. Using a coordinated set of high-resolution sectoral assessment tools, we report a decrease of 4.2% in global CO_2 emission in first quarter of 2020. Our emission estimates reflect near real time inventories of emissions from power generation, transportation, industry, international aviation and maritime sectors in 34 countries that account for >70% of world energy-related CO2 emissions in recent years. Regional variations in CO_2 emissions are significant, with a decrease in China (-9.3%), US (-3.0%), Europe (EU-27 & UK) (-3.3%) and India (-2.4%), respectively. The decline of short-lived gaseous pollutants, such as NO_2 concentration observed by Satellites (-25.73% for China, -4.76% for US) and ground observations (-23% for China) is consistent with the estimates based on energy activity (-23.94% for China, -3.52% for US), but the decline is not seen in satellite assessments of aerosol optical depth (AOD) or dry column CO_2 (XCO_2). With fast recovery and partial re-opening of national economies, our findings suggest that total annual emissions may drop far less than previously estimated (e.g., by 25% for China[1] and more than 5% for the whole world[2]). However, the longer-term effects on CO2 emissions are unknown and should be carefully monitored using multiple measures.

Introduction

COVID-19 had decimated economies worldwide, with some countries spiking from 3~4 % to over 30% in just weeks[3,4]. Initial estimates based on selected power plants and the satellite observation suggested[1,2] that related decreases in global CO2 emissions could be the largest since the end of the Second World War. However, thorough quantitative analyses of the pandemic's effects on energy use and emissions are yet lacking[5]. This is largely because well-known published datasets of greenhouse gas emissions are based on annual statistics which commonly lag behind by one or more years[6-11]. A high temporal resolution emission dataset is critical to capture the immediate effects of an event like the COVID-19 pandemic. Such improved resolution might also allow policy makers to more quickly observe the effects of policies aimed at decreasing CO_2 emissions, facilitating rapid adjustments.

Here, we present a newly developed, near real time global emission dataset that estimates monthly and weekly energy consumption and associated CO2 emissions, and use this dataset to estimate the impact on CO2 emission trends due to COVID-19. The dataset was compiled from monthly and weekly energy statistics and industrial products by sectors at the global scale, cross-checking and comparing the estimates with independent measurements of CO2 and air quality from satellites and ground observations. We show that the higher resolution emission dataset can be used to assess the impact of COVID-19 (and similar future disruptions) within a reasonable range of uncertainty.

Emission estimated by inventories

The global CO2 emission by first quarter of 2020 is calculated by the monthly, weekly, daily and hourly energy consumption statistics and proxy industrial products data of individual sectors (See methods and SI Data Table 1 for data sources). Globally 34 countries including China, US, UK, 27 Europe countries (EU27: Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden), Russia, Japan, Brazil and India are calculated as well as the international aviation and maritime emissions that contribute 70% of the global total emissions in 2019.

The results show a 3.8% decrease of the calculated countries' CO_2 emission in the first quarter of 2020 when comparing with the period of 2019, with another 0.4% decrease of global total emission from international aviation and maritime emissions (Table 1). This is mainly contributed by China (-9.3%), US (-3.0%), Europe (EU27 & UK) (-3.3%) and India (-2.4%), respectively. For the perspective of sectoral emissions, the decline of global CO_2 emissions is contributed by transport sector (-6.0%, -121.7 $MtCO_2$), power sector (-3.3%, -111.2 MtCO2) and industry sector (-4.9%, -78.1 $MtCO_2$). Total emission reduction in first quarter comparing with the last year reached -310.9 $MtCO_2$, which is still lower than the annual emission decline around the economic crisis of 2008. China as the country with early pandemic reached largest emission reduction of -217.0 $MtCO_2$, followed by US (-41.2 $MtCO_2$), Europe (EU27 & UK) (-26.2 $MtCO_2$) and India (-13.9 $MtCO_2$).

Table 1. Emission decline and changes by countries/regions in the first quarter in 2020.

(See SI Table 1 for full sectoral changes by countries/regions)

Unit: MtCO2	Sectoral Changes			Summary	**Growth Rates (%)**
	Power	Transport	Industrial		
China	-75.7	-83.1	-58.1	-217.0	**-9.3%**
India	2.9	-6.1	-10.7	-13.9	**-2.4%**
US	-21.7	-11.7	-2.3	-35.8	**-3.0%**
EU	-7.0	-16.2	-3.0	-26.2	**-3.3%**
Russia	-4.4	0.0	1.1	-3.3	**-0.8%**
Japan	-5.1	-1.0	-4.5	-10.6	**-3.8%**
Brazil	-0.2	-3.5	-0.5	-4.2	**-3.9%**
Summary	**-111.2**	**-121.7**	**-78.1**	**-310.9**	**-3.8%**
International aviation	-	-	-	-19.8	**-8.0%**
International shipping	-	-	-	-35.5	**-13.3%**
World	-	-	-	**-366.2**	**-4.2%**

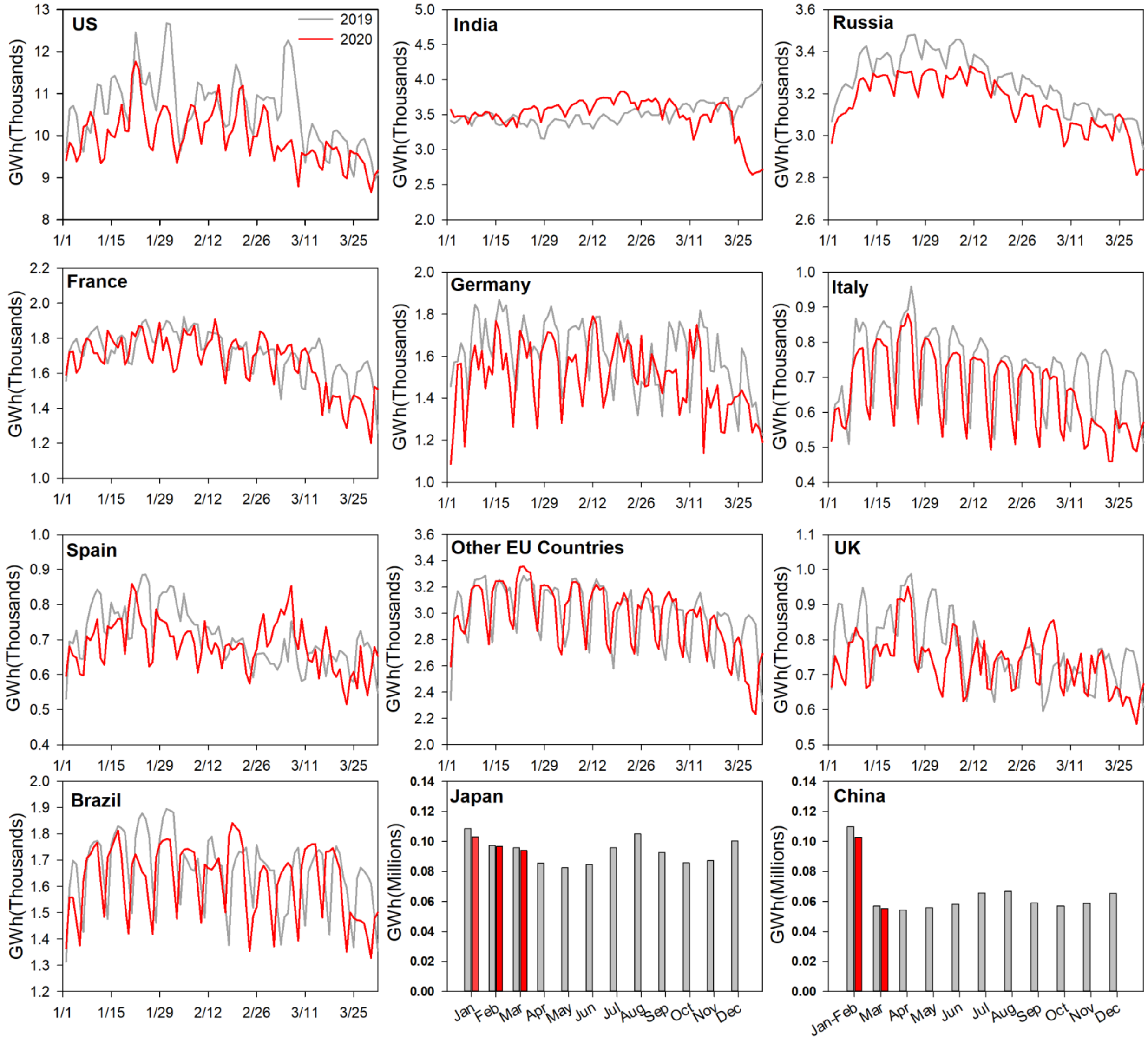

Fig 1. Daily/monthly electricity generation in 2020 in US, India, Russia, France, Germany, Italy, Spain, other EU countries (Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, Greece, Hungary, Latvia, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, and Sweden), UK, Brazil, Japan and China. (See SI Table 2)

Power sector (See Methods for data and calculation process) is the key consumer for global fossil fuel consumption (account 40% of global fossil emission), especially for coal. Emission decrease by power estimated directly by near real time electricity generation that covers the data from monthly to hourly (See

Methods), which are compiled from publications of government, electricity association or companies. The results show the largest decline in total and percentage of the emission in China (Figure 1). The official reported data show the -8.2% reduction of electricity generation in China in January and February together, and -4.6% reduction in March, when comparing with the same period last year. The decrease of electricity generation is more obvious in March in other regions in consistent with the pandemic of COVID-19. In US the electricity generation decreased with -6.7% in March, and France, Germany, UK and Italy decreased by -4.7%, -8.2%, -0.9% and -14.5% respectively. There is also sharp decrease in India by 8.7% in March. In the first quarter, global CO_2 emissions in power sector have declined by -3.3% (-111.2 $MtCO_2$), in against -6.8% (-75.7 $MtCO_2$) in China, -4.9% (-21.7 $MtCO_2$) in US and -2.5% (-7.0 $MtCO_2$) in Europe (EU-27 & UK), but slightly increased in India by +1.0% (+2.9 $MtCO_2$) (See SI Data table 2.1 and 2.2)

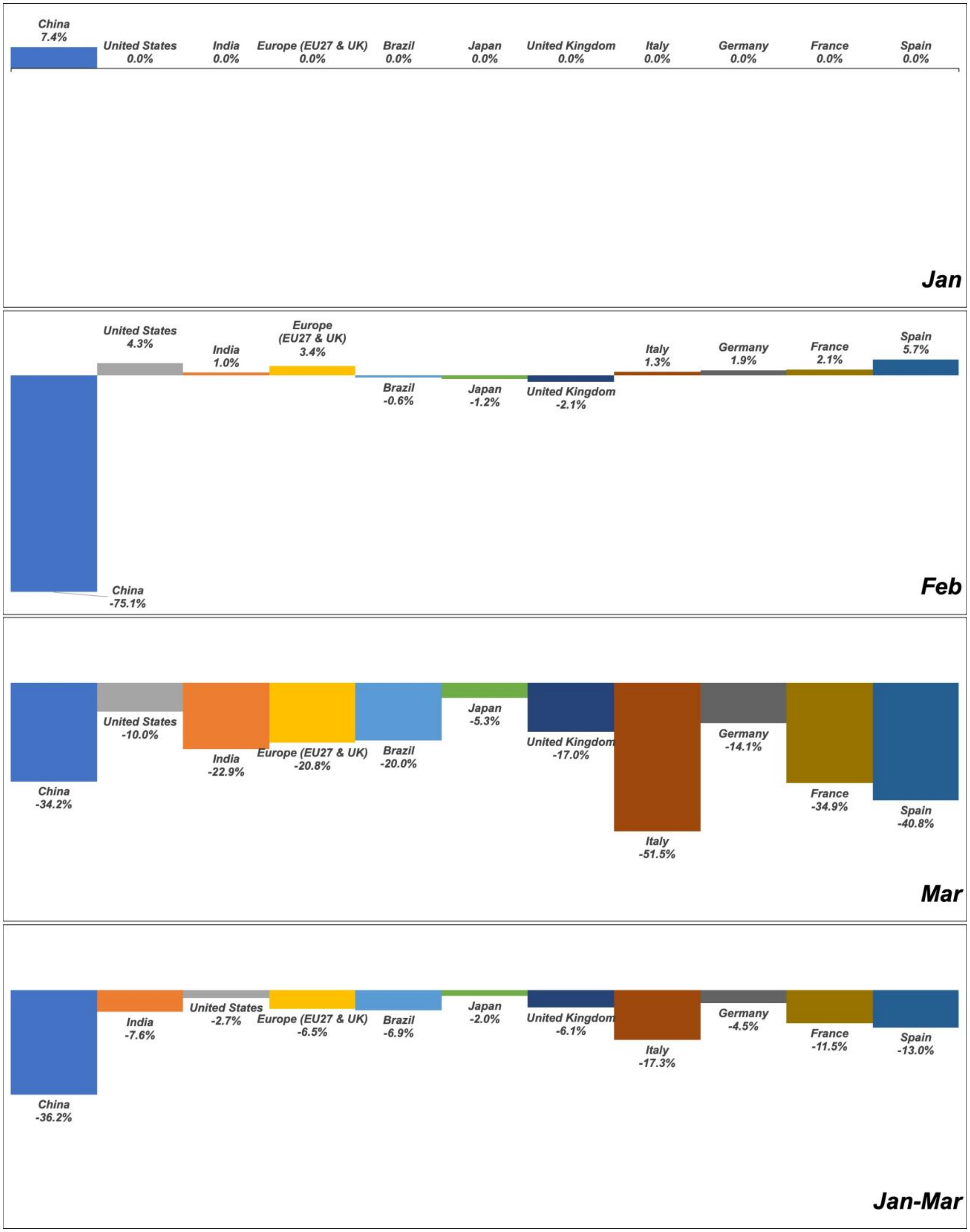

Fig 2. Monthly emission changes in transport sector in February, March and the first quarter of 2020. (See SI Table 3)

Transport sector (See Methods for data and calculation process) contributes the second largest share (25%) of the world total emissions but contributes mostly in the decline of total emission (6.0%, 121.7 $MtCO_2$) in first quarter in 2020 (Figure 2). Emissions from transport sector are calculated based on the mobility collected from Google Mobility Reports and Baidu Migration Scale Index during the period (See Methods and SI Data Table 3.1-3.3). In China, even though cities started locking down since the last week in January, the emissions from transport have still increased by +2.6% due to an earlier start of the Spring Festival travel rush in 2020 when comparing with same period last year. However, since February, the emissions from transport have dropped significantly, by -75.1% in February and -34.2% in March. In the first quarter of 2020, the emissions from transport have dropped -37.2% (-83.1 $MtCO_2$) in China. Since the pandemic has spread worldwide in March, the emission from transport have dramatically decreased in other countries. Emissions in US and India have dropped by -10% and -22.9% in March. Emissions in European countries have fell by an average of -22.8% in March, while Italy and Spain have decreased most by -51.5% and -40.8% respectively. In the first quarter of 2020, emissions in US, India and Europe (EU27 &UK) have dropped -2.7% (-11.7 $MtCO_2$), -7.6% (-6.1 $MtCO_2$), -7.3% (-16.2 $MtCO_2$) respectively.

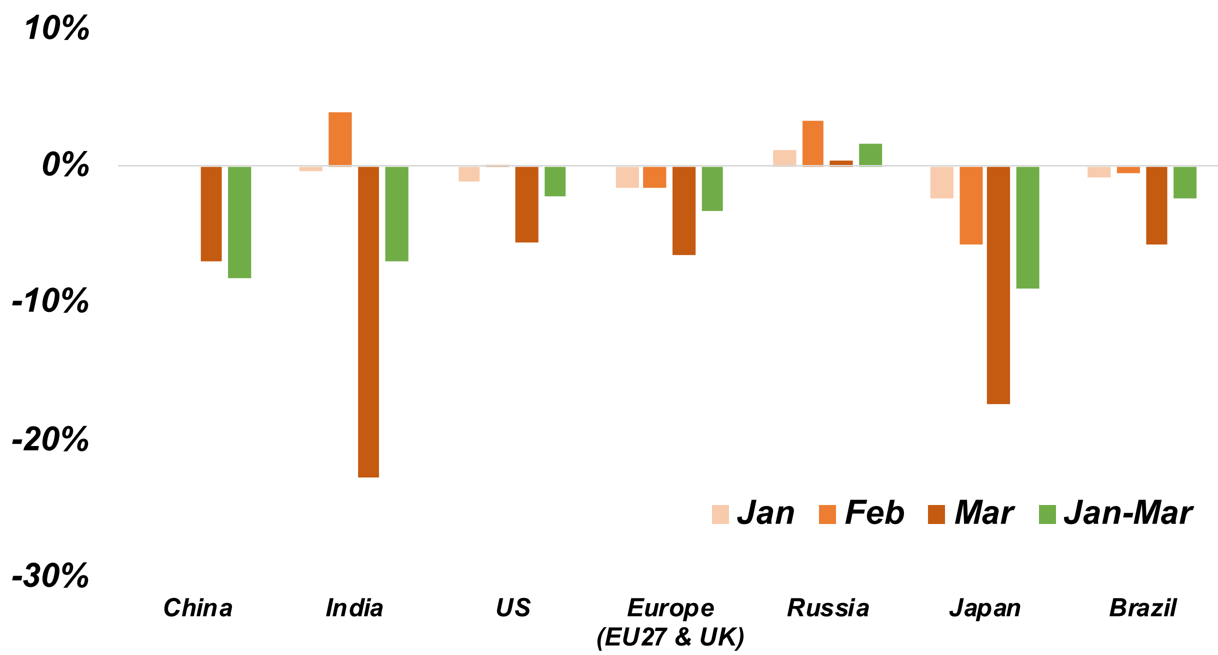

Fig 3. Monthly emission changes in industrial sector by countries/countries. (See SI Table 4)

Emissions from manufacturing, processing, chemical industry and other industrial activities are calculated together as Industrial Sector that contributes 24% of the total CO_2 emissions, but its shares are much larger in developing countries, i.e., 29.8% in China and 26.1% in India. Thus, separated data on steel industry, cement industry, chemical industry and other industry are collected for China and India for more accurate estimation (SI Data Table 4.1-4.5). In the first quarter of 2020, the industrial emissions have declined by -7.0%, -2.2%, -3.2% respectively in India, US and EU, with the largest decline in March by -22.6%, -5.5%, and -6.4% respectively (Figure 3, SI Data Table 4.1-4.5). In China, the largest decline occurred in the first two months in 2020 by 9-.8%, and have fell by -8.1% in the first quarter of 2020. The emissions from steel industry are 41.6% of the total industrial emissions in China. Compared to the same periods of last year, the emissions from steel industry in China have increased +1.4% and +5.0% in

January and February but dropped -1.7% in March, however, the emissions from steel industry still grow +1.4% in the first quarter in 2020. For the cement industry, China official reports show declines of -29.5% in January and February together and -18.3% in March. For the first quarter in 2020, the emissions from cement industry in China has dropped -23.9%. Emissions from chemical industry in China have also decreased by -4.2%. For other industry in China, the emissions have fell by -13.6%.

Emissions from steel industry in India also accounts for over 47% of the total industrial emissions, and the emissions have decreased by -13.9% (-3.9 $MtCO_2$) in March and -5.3% (-4.5 $MtCO_2$) in the first quarter in 2020. Emissions from cement industry in India have dropped -10.2% in the first quarter. In the first quarter of 2020, the global emissions from industrial sector have fell by -4.9%, with the contribution by China (-8.1%, -58.1 $MtCO_2$), US (-2.2%, -2.3 $MtCO_2$), EU & UK (-3.2%, -3.0 $MtCO_2$) and India (-7.0%, -10.7 $MtCO_2$).

The number of flights decreased significantly in February and March. Our results about weekly emissions from international aviation (See Methods for data and calculation process) show that international aviation emissions have increased +0.8% (+0.7 $MtCO_2$) in January and dropped -8.6% (-6.9 $MtCO_2$) and -15.2% (-13.6 $MtCO_2$) in February and March respectively. The international aviation emissions have decreased by -8.0% (-19.8 $MtCO_2$) in total in the first quarter of 2020. In China, the international aviation emissions in February and March have significantly dropped by -55.2% (-3.2 $MtCO_2$) and -40.1% (-2.4 $MtCO_2$) respectively. Elsewhere, the decline has been particularly significant in March. In March, the international aviation emissions in US have decreased by -2.2% (-0.3 $MtCO_2$), the emissions in Europe such as in UK and Italy have dropped by -23.7% (-1.3 $MtCO_2$) and -49.3% (-0.9 $MtCO_2$) respectively, and the emissions in Asia such as in Japan and South Korea have declined by -16.8% (-0.5 MtCO_2) and -49.7% (-1.1 MtCO_2) respectively. However, the emissions in India still grow in the first quarter in 2020, when comparing with same period last year.

Global shipping CO_2 emissions (See Methods for data and calculation process) have decreased by -13.3% (-35.4 Mt CO_2) in the first quarter of 2020 compared to the same period in 2019. Emissions from container ships and bulk carries ships decreased by -15% (-9.2 Mt CO_2) and -25.8% (-13.1 Mt CO_2), respectively. Emissions from oil tankers ships increased by +2.2% (+0.8 Mt CO_2) due to the decline in international oil prices. Emissions from other 19 ship classes were reduced by -11.5% (-13.9 Mt CO_2).

The observation of air quality and dry column CO_2 (XCO_2)

The results of tropospheric nitrogen dioxide (NO_2) column concentration data from satellite observation and surface air quality data by ground monitoring sites have exhibited a similar decreasing trend with global CO_2 emissions. We collected NO_2, aerosol optical depth (AOD) and column-averaged dry air mole fraction of CO2 (XCO_2) data from satellites (NO_2 from OMI, AOD from MODIS and XCO2 from GOSAT) and the global surface daily average nitrogen dioxide (NO_2, $\mu g/m^3$), carbon monoxide (CO, $\mu g/m^3$), and air quality data in China and US to investigate the plausible impact of COVID-19 on air quality and atmospheric CO_2.

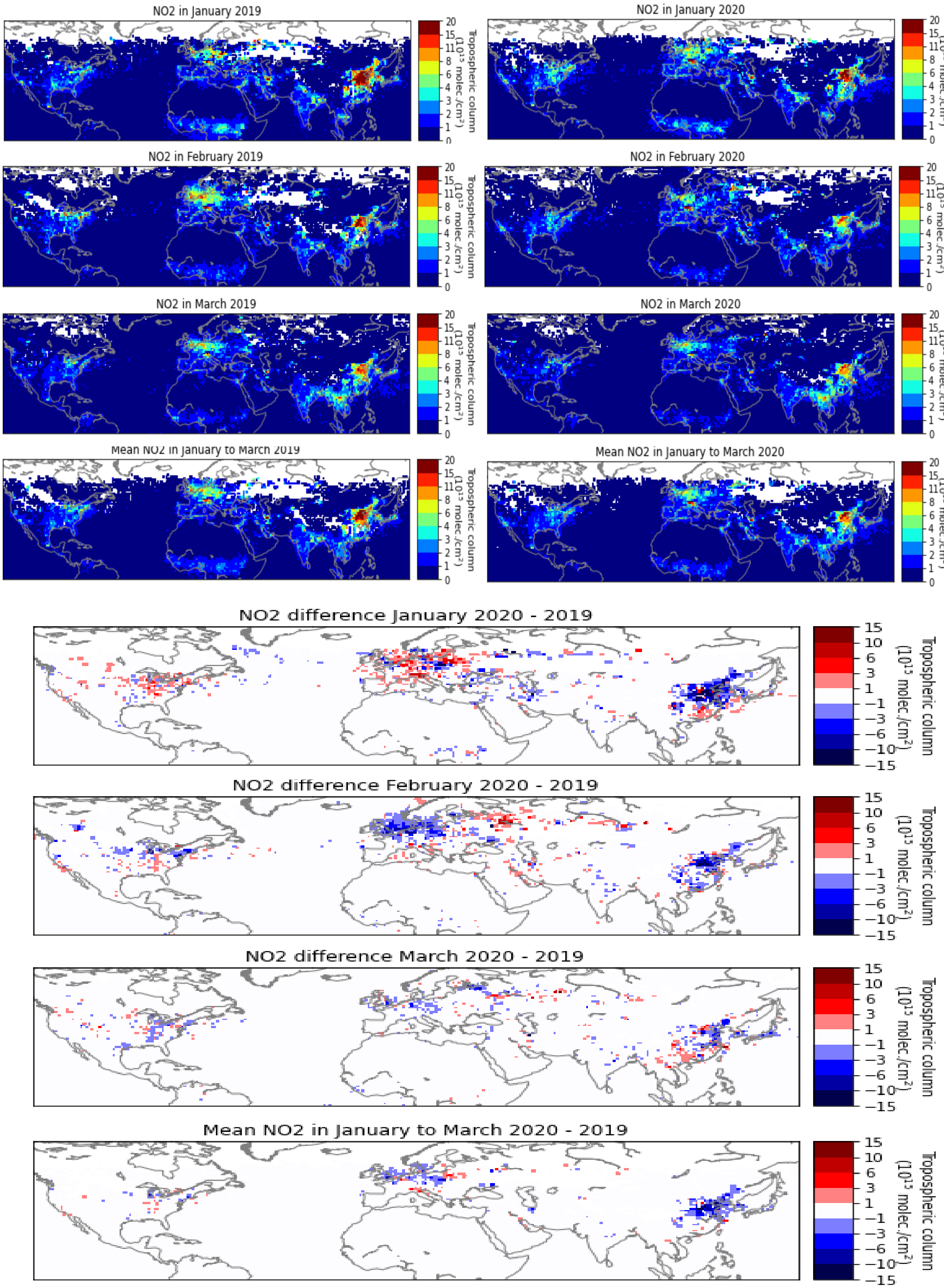

Fig 4. Tropospheric column NO_2 Observation in the first quarter of 2020.

Surface air quality data in China is collected from the daily report by Ministry of Ecology and Environment of China (http://www.mee.gov.cn/). Measurements of daily average nitrogen dioxide (NO_2, μg/m^3), carbon monoxide (CO, μg/m^3), and particulate matter smaller than 2.5 μm ($PM_{2.5}$, μg/m^3) from 1580 sites are used to estimate pollution changes between the first quarters of 2019 and 2020. Surface air quality data in U.S. is downloaded from the Air Quality System (AQS) operated by the U.S. Environmental Protection Agency (https://www.epa.gov/aqs). Measurements of daily maximum 1-hour NO_2 (ppb), daily maximum 8-hour CO (ppm), and daily average $PM_{2.5}$ (μg/m^3) from 983 sites are used. For March 2020, data availability is limited in U.S. with 20 sites for NO_2, 31 for CO, and 309 for $PM_{2.5}$. Sites with missing data for NO_2/CO ($PM_{2.5}$) at over 20 (5) days in any months will be excluded.

Table 2 shows the NO2 decrease in 2020 compared to 2019 over each country in each month. In China, January, February, and March 2020 decreased by -32.27%, -34.22%, -4.53% respectively compared to 2019. Overall, NO_2 decreased by -23.67% in the first quarter of 2020 compared to 2019. We notice that a rapid drop appeared in February 2020 for China (Figure 5d), which is greater than two sigma ($\sigma = 45.053 \times 10^3 molec\ km^{-2}$), and NO_2 decrease remained in February and March Such a significant NO_2 drop rarely appeared in the previous years except for Jan 2018. However, the decrease in Jan 2018 did not last more than a month, indicating the continuous decrease of NO_2 from Jan – March in China were associated with COVID-19. In US, the decrease of NO_2 at first appeared in Feb and stayed decreasing in March 2020 (Figure 5d). Compared to the same time in 2019, NO_2 decreased by -23.08% and -14.32% in February and March 2020, respectively (Table 2). EU4 (UK, France, Germany, and Italy) holds the similar changes as the USA for NO_2. The US and EU4 statistics in NO_2 seem to reflect ~ one-month delay of COVID-19 outbreak in the western countries. India had weaker decline in NO_2 than other regions. The epidemic situation in India even lags behind US and EU4. No cases have been reported in India until March 2 and there were only 1,834 cases until April 1. Thus, the drastic decrease of NO_2 in the first quarter of 2020 is very likely associated with transportation and industry shutdown due to COVID-19.

Table 2 Changes of 2020 compared to 2019

		China	US	EU4	India
OMI NO2	January	-32.26% ± 12.03%	22.98% ± 16.02%	15.78% ± 15.24%	-8.96% ± 13.63%
	February	-34.22% ± 11.87%	-23.08% ± 12.63%	-25.12% ± 12.40%	-13.79% ± 13.36%
	March	-4.53% ± 13.77%	-14.32% ± 13.24%	-15.56% ± 13.22%	-13.37% ± 13.29%
	January-March	-25.73% ± 12.51%	-4.76% ± 13.75%	-9.71% ± 13.54%	-11.99% ± 13.47%
MODIS AOD	January	10.17% ± 49.22%	10.64% ± 95.67%	19.81% ± 77.76%	-5.46% ± 36.27%
	February	-7.88% ± 41.08%	-3.98% ± 82.64%	-1.95% ± 70.78%	7.29% ± 39.89%
	March	3.55% ± 41.88%	-15.65% ± 67.37%	29.42% ± 62.28%	1.84% ± 41.12%
	January-March	1.26% ± 44.04%	-5.08% ± 79.02%	17.51% ± 69.42%	0.81% ± 38.88%
GOSAT XCO2	January	0.53% ± 0.52%	0.60% ± 0.52%	0.42% ± 0.52%	0.65% ± 0.52%
	February	0.45% ± 0.51%	0.53% ± 0.52%	0.65% ± 0.52%	0.44% ± 0.51%
	March	0.67% ± 0.52%	0.37% ± 0.52%	0.51% ± 0.52%	0.66% ± 0.52%
	January-March	0.55% ± 0.52%	0.50% ± 0.52%	0.52% ± 0.51%	0.58% ± 0.52%
TROPOMI CO	January	2.67%±5.20%	4.94%±3.02%	2.37%±1.89%	-0.41%±3.37%
	February	0.47%±7.11%	2.97%±3.91%	1.08%±2.33%	3.23%±5.20%
	March	3.98%±6.77%	-1.84%±3.39%	-1.14%±3.10%	2.12%±3.45%
	January-March	2.38%±4.84%	1.85%±1.94%	0.72%±1.40%	1.66%±2.38%
Site NO2	January	-18.05%±23.90%	-3.80%±12.80%		
	February	-30.33%±21.78%	14.98%±68.82%		
	March	-23.03%±17.29%	-8.98%±44.17%		
	January-March	-23.00%±14.97%	0.34%±79.05%		
Site PM2.5	January	-2.67%±41.56%	-8.77%±49.43%		
	February	-26.71%±26.94%	-14.78%±59.12%		
	March	-21.80%±17.51%	-20.55%±39.30%		
	January-March	-15.39%±19.06%	-14.68%±40.49%		

Site CO	January	-5.89%±22.22%	-12.35%±23.12%
	February	-19.60%±20.49%	-6.19%±45.39%
	March	-14.24%±19.77%	4.94%±74.21%
	January-March	-12.51%±15.41%	-5.11%±26.53%
Inventory NO2	January		-0.99% (-1.36~-0.86%)
	February		2.43% (2.11~3.33%)
	March	-15.49% (-21.20~-13.46%)	-7.72% (-10.58~-6.72%)
	January-March	-17.47% (-23.94~-15.20%)	-2.57% (-3.52~-2.24%)

The decline rate of NO_2 (-25.73%) based on observation could be used to compare with the NO_2 emission decreases that calculated based on inventory, so to reveal whether the change in CO2 emissions for sectors is consistent with the decrease of tropospheric NO_2 column concentration. For China where the most significant decrease of tropospheric NO_2 column concentration overserved, we further calculated the decline rate of NO2 emission in first quarter of 2020 based on China's annual NO2 emission inventory[12] and the change of rates of Power generation (-6.8%), Transportation (-37.2%) and Industry(-8.1%) in first quarter of 2020 when comparing with the period in 2019. These three sectors together account for 96% of China's total NO2 emissions, and the calculated emission decline in first quarter of 2020 is -23.94% or -15.20% when an additional -5% annual rate of emission factors adopted due to the implementation of denitrification measures[13]. The -23.42% decline of the NO_2 emissions is well consistent with the satellite observation of -25.73% of the satellite observation of NO_2, and also well consistent with the decrease of average number (-23.00%) by 1680 site observation of surface NO_2 concentration yet the uncertainty with two assessments need be considered. For US, the change of rates of Power generation (-4.9%), Transportation (-2.7%) and Industry(-2.2%) are adopted with result of -2.57% NO2 emission in first quarter of 2020 when comparing with 2019, and the -2.57% is also well consistent with -4.76% tropospheric NO_2 column concentration, but difference with the site observation data (-8.98% in March and +0.34%for first quarter), which may be affected by site numbers (only 20sites in US).

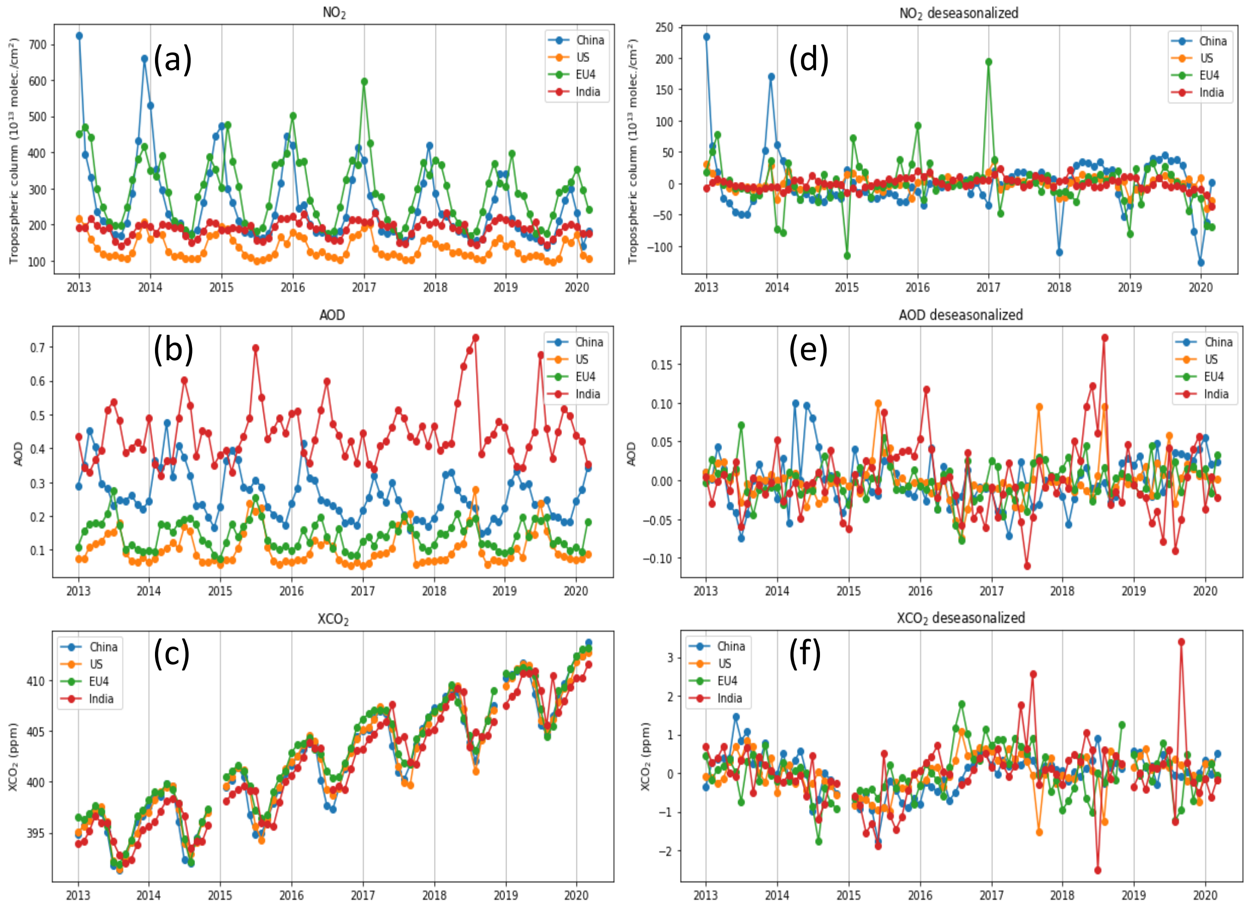

Figure 5. Left panels (a-c): the monthly series of NO_2, AOD and XCO_2 over China, US, EU4 (UK, France, Germany, and Italy), and India; Right panels (d-f): de-trended and de-seasonalized time series.

On the contrary, we do not see clearly impact of COVID-19 on AOD and XCO_2 for those regions. The lifetime of NO_2 in the atmosphere is about 52 minutes[14], aerosols last days to weeks[15], and CO_2 is over 100 years[16]. We expect some delays in AOD and XCO_2 if any impact of COVID-19 exists. However, China has controlled the epidemic within two months, we may not be able to see changes in AOD and XCO due to their longer lifetime greater than two months. The extended monitoring beyond the pandemic can validate these theories. Moreover, aerosol formation, transformation, and removal processes are highly complex[17,18], which make aerosol atmospheric burdens highly non-linear with the emissions of their precursor gases, like NO_2.

Uncertainty

CO_2 emission show liner relationship with the energy consumption in most countries, and thus the uncertainty of using proxy data to assess the growth rate is well within the uncertainty of the statistical data itself. Previous estimates quantified the uncertainty of $\pm$20% for carbon emission in emerging economics and $\pm$5% for global average[15], however, the projections of emission growth based on GDP or monthly energy statistics show larger uncertainty, for example, the initial emission estimates of China based on Monthly statistics result in a 4.8% growth in 2018 with uncertainty range expand from 1.3% to 8.3% by considering the uncertainty from both the energy statistics and the emission factors, here we conservatively considered the same uncertainty range from previous emission estimates that based on the monthly statistics and Monte Carlo simulation of 10000 trials to estimate the 68% confidence interval (i.e., one sigma range) for China (See Methods). The consistence of the results shows robust about the calculation of one year's growth rate based one the monthly statistics (Figure 6).

For satellite observations, the overall uncertainty of tropospheric NO2 columns monthly mean is 10%[19]. The uncertainty of AOD is approximately $0.03+0.20\tau_M$, where τ_M is AOD at 550 nm[20]. In other words, the uncertainties in percentage in low AOD regions (US and EU4) is higher in high AOD regions (China and India). The standard deviations of XCO_2 monthly mean over land are about 0.5-1.5 ppm[21].

Here we conservatively considered uncertainty of monthly XCO_2 as 1.5 ppm. To estimate the uncertainty of changes of 2020 compared to 2019 from January to March, we input above uncertainties of monthly means and run Monte Carlo simulations of 10000 trials to calculate the 68% confidence intervals (i.e., one sigma range) which are shown in Table 1.

Discussion

It is still unclear how much the global CO2 emission will change at the end of this year, and how fast the economic and industry will resume back to normal. With the policy support, economy will be stimulated since the pandemic fade. IMF predicts the global annual economic output will decrease sharply by -3.0% in 2020 which is worse than the financial crisis in 2008 [22], based on the assumption that the COVID-19 will fade globally in the second half of this year. The emission decline is estimated to be less than 5%, and the future trend will be affected by the pandemic in Europe and US. Current statistics is still not capable to comprehensively capture the dynamics of the CO2 emission under the COVID19 pandemic and further monitoring, observation and data collecting are urgent needed.

Methodology

1) CO2 emission data in 2019.

The CO2 emissions and sectoral structure in 2017 for countries and regions are extracted from International Energy Administration (IEA)[23], and the emissions are scaled to 2018 and 2019 based on the growth rates from EDGAR[9] and Global Carbon Budget 2019[24] respectively. For countries with no current estimates of emission growth rates in 2019 such as Russia, Japan and Brazil, we assume their growth rates of emissions were 0.5% based on the emission growth rates of rest of world from Global Carbon Budget 2019[24].

Given the large uncertainty of CO_2 emission in China[25,26], we calculated the CO_2 emissions in China based on the methodology developed[27] previously:

$$\text{Emissions}= \sum\sum\sum(Energy\ consumption\ data_{i,j,k} \times Emission\ factors_{i,j,k}) \quad (1)$$

i, j, k reflect the regions, sectors and fuel types respectively. In our calculation, i covers XX countries that representing 70% of global total emissions. j covers four sectors that are power generation, industry, transportation and household consumption, k covers three primary fossil fuel types which are coal, oil and natural gas. Emission factors can be further separated into the net heating values for each fuel “v”, the energy obtained per unit of fuel (TJ per t fuel), the carbon content “c” (t C TJ-1 fuel) and the oxidization rate “o”, which is the fraction (in %) of fuel oxidized during combustion and emitted to the atmosphere.

$$\text{Emission} = \sum\sum\sum(Energy\ consumption\ data_{i,j,k} \times v_{i,j,k} \times c_{i,j,k} \times o_{i,j,k})$$

We assume the emission factors and the structure remain unchanged for each country in 2020 when comparing with 2019. Thus, the rate of change of the emission is calculated based on the change of the energy consumption in 2020(for first quarter) when comparing the 2019.

CO_2 emission show liner relationship with the energy consumption in most countries, and thus the uncertainty of using proxy data to assess the growth rate is well within the uncertainty of the statistical data itself. Previous estimates quantified the uncertainty of $\pm$20% for carbon emission in emerging economics and $\pm$5% for global average[15]. For uncertainty of using monthly, weekly or hourly proxy statistics of activity data(power generation, industrial output etc.) to calculated the growth rate emission for whole year, we adopted the uncertainty range based on the estimates of annual emission by monthly statistics in China[28]. This is a conservatively estimation given that the data and statistics in China is considered to be one of the largest in the world. We calculated the 68% prediction interval of these linear regression models and used them to reflect the one-sigma uncertainty involved when using the monthly data to represent the whole year's variation (figure 6). The squared correlation coefficients are within the range of 0.88 (e.g., coal production) and 0.98 (e.g., energy import and export data), which represent that only using the monthly data can explain 88% to 98% of the whole year's variation[28], while the remaining variation not covered yet reflect the uncertainty caused by the frequent revisions of China's statistical data after they are first published. Such conservative calculation result in +-73% of the uncertainty range (one sigma).

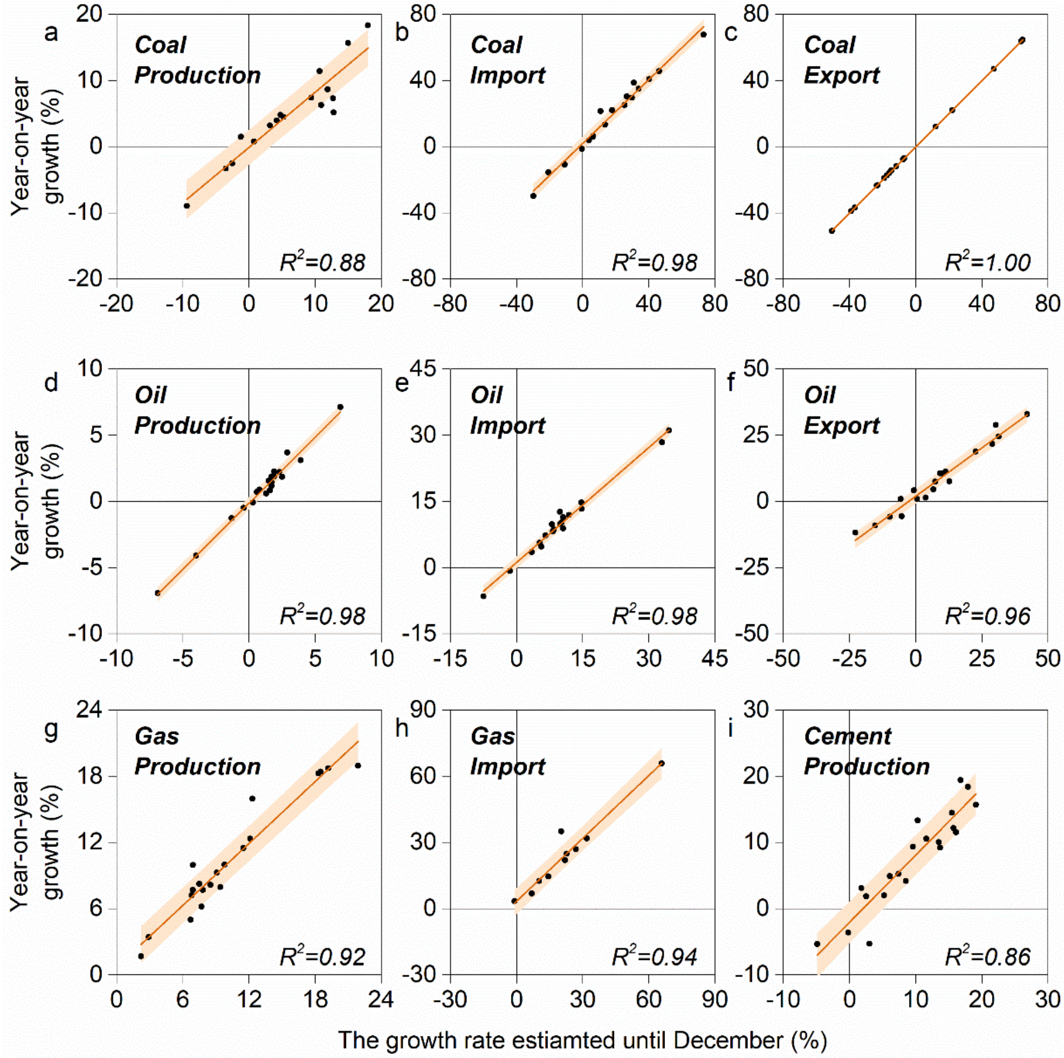

Figure 6. Correlation between the growth rates of monthly statistics with those from the whole year between 1990 and 2018. The x value is certain year's growth rate that calculated based on monthly statistics of the year, the y value is the growth rate for whole year. The consistence of the results shows robust about the calculation of one year's growth rate based one the monthly statistics.

2) CO_2 emission change rates in 2020 when comparing with 2019.

Based on the assumption of sectoral carbon intensity and energy structure remain unchanged from 2017, we scale the sectoral CO_2 emissions to 2020 by using proxy data for sectors:

For power generation:

For China and Japan, only monthly electricity generation statistics are available on the National Bureau of Statistics in China (http://www.stats.gov.cn/tjsj/). However the latest observation in Japan was in February 2020. We collect the daily electricity generation data from four electricity company (Hokkaido Electric Power Co., Inc., Tohoku Electric Power Network Co., Inc., TEPCO Power Grid, Incorporated, Chubu Electric Power Grid Co.,Inc., and Hokuriku Electric Power Transmission & Distribution Company) in Japan, which accounts for around 50% of the total generation, and calculate the monthly growth rate in March to scale the total electricity generation data to March in Japan. For US, daily total electricity generation data of the Lower 48 states are collected from Energy Information Administration's (EIA) Hourly Electric Grid Monitor (https://www.eia.gov/beta/electricity/gridmonitor/). For EU countries and UK, electricity generation data every 15 minutes by production types are collected from ENTSO-E Transparent platform (https://transparency.entsoe.eu/dashboard/show). Due to the poor data quality or missing data, Croatia, Cyprus, Ireland, Luxembourg and Malta are excluded in the calculation. The hourly data of the other 23 EU countries (including Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden) and United Kingdom are aggregated into daily total electricity generation data. For India, daily total electricity generation data are updated by Power System Operation Corporation Limited (https://posoco.in/reports/daily-reports/). For Russia, daily electricity generation data are collected from United Power System of Russia. For Brazil, daily electricity generation data are downloaded from the Operator of the National Electricity System (http://www.ons.org.br/Paginas/). All the daily electricity generation data are further aggregated into monthly data to calculate the monthly growth rates. For the monthly emissions in 2019, we use the monthly electricity generation for countries to allocate the emissions in power sector for each month. Then we calculate the monthly emissions in 2020 based on the monthly growth rates compared to the same periods in 2019.

For Transportation:

The mobility trends from the Google COVID-19 Community Mobility Reports (https://www.google.com/covid19/mobility/) are mainly used in this study. The mobility changes are calculated based on the visits and visit duration in six places categories, including grocery & pharmacy, parks, transit stations, retail & recreation, workplace, and residential. The daily mobility changes are compared to the median value during the first five weeks in 2020 for the corresponding day of the week as the baseline value. Except for residential, we consider that the mobility change of visits in the other five places representing the total mobility, so we calculate the daily average mobility change of five of the place categories to represent as the changes of the total traffic volume in these countries, based on the assumption the mobility in the same period in 2019 and January in 2020 is at the same level of the baseline value. The average mobility of EU countries except for Cyprus (lack of data) is used to estimate the emission growth in EU countries.

In China, we use the change of the Baidu Migration Scale Index to characteristic the change of transport sector, due to the lack of data in Google Community Mobility Reports in China. This index is aggregated from migration flows within the nation based on the positioning requests on Baidu Map services. The migration scale index is reported since Jan. 12th in 2019 and Jan. 1st in 2020, 9 days before the start of the Spring Festival travel rush every year. To fill the data gap between Jan. 1st 2019 to Jan. 11th, 2019, we use the average value of migration index between Jan. 12th, 2019 and Jan. 20th, 2019. Then we aggregate the daily index into monthly total and calculate the monthly changes in 2020 compared to 2019.

In Russia, because the lack of data and the earliest lockdown policy implementing on Mar. 30th in Moscow, we assume that the transport emissions remain unchanged in the first quarter in 2020.

For Industry:

For China, the industrial sector is divided into four industries including steel industry, cement industry, chemical industry, and other industry. For the steel industry, we collect the global monthly crude steel production data from World Steel Association (https://www.worldsteel.org/). For cement industry, China's monthly cement production data are available on the National Bureau of Statistics. We estimate the growth rate of chemical production in China chemical industry by calculating the average cumulative growth rates of sulfuric acid, caustic soda, soda ash, ethylene, chemical fertilizer, chemical pesticide, primary plastic and synthetic rubber. For other industry, we estimate the change in China other industry by calculating the average cumulative growth rates of 26 industrial products (crude iron ore, phosphate ore, salt, feed, refined edible vegetable oil, fresh and frozen meat, milk products, liquor, soft drinks, wine, beer, tobaccos, yarn, cloth, silk and woven fabric, machine-made paper and paperboards, newsprint, plain glass, ten kinds of nonferrous metals, refined copper, lead, zinc, electrolyzed aluminum, industrial boilers, metal smelting equipment, and cement equipment). Based on the emission distribution of these four industries in industrial sector in China, we finally get the annual growth rate of industrial sector in China.

For US and Russia, we use the cumulative Industrial Production Index (IPI) from Federal Reserve Board (https://www.federalreserve.gov) and Federal State Statistics Service (https://eng.gks.ru) respectively, to estimate the growth rates of the emissions in these countries.

For India, the industrial sector is divided into steel industry, cement industry, and other industry. Emissions from steel industry and cement industry account for 60% of the total emissions in industrial sector of India. The steel production in India is extracted from World Steel Association. India's monthly cement production data could be found from the Office of the Economic Advisor, but the last observation was on February. We assume that the cement production in India has dropped 40% in March. For other industry, we assume the growth rate is the average of growth rates of steel production and cement production.

For EU27, UK, Japan and Brazil, we use the cumulative Industrial Production Index (IPI) to estimate the growth rates of emissions in these countries or regions. However, the last observation in EU27 and UK was in January 2020 and those in Japan, Russia and Brazil were in February 2020. To estimate the current growth in March 2020, for EU27 and UK, we assume that the monthly growth rate in February 2020 equals to that of the same month in 2019. The monthly growth rate in March 2020 in EU27 and UK together has fell 5%, based on the assumption of the average growth rate of industrial sector in China (-8.1%) and US (-2.2%) because of the implement of locking down policies later than China but earlier than US. For Japan and Brazil, as looser travel restriction in these countries, we assume the monthly growth rates in March were -3% compared to February.

For international aviation:

The International Council on Clean Transportation (ICCT)[29] published that CO2 emissions of commercial aviation from international passenger movements totaled 444 Mt in 2018 and implied annual compound growth rate of total emissions from commercial flights, 5.7%, during the past five years from 2013 to 2018[1]. Sub-national CO2 emissions from international passenger operations based on the location of flights departing airports are provided by ICCT. It is known that total CO2 emissions from all commercial operations include passenger movement, belly freight, and dedicated freight. ICCT published that passenger transport accounted for 81% of total emissions in 2018, so we use this proportion to estimate the international aviation emissions from commercial flights in 2018. Due to the lack of emissions data after 2018, We use the compound growth rate of commercial aviation emissions, 5.7%, to estimate the international aviation emissions from commercial flights in 2019. Based on the assumption that the number of international commercial flights and the number of total commercial flights including domestic and international flights have the same distribution over time, we collect the number of sub-national commercial flights for each week in the first quarter in 2019 and the same week in 2020 from OAG to estimate international aviation emissions from commercial flights for each week during this period. Daily tracking statistics about commercial flights and total flights in 2020 are provided by Flightragar24, which are collected to estimate the international aviation emissions from total flights in the first quarter in 2020 according to the proportion of the number of total flights and commercial flights. Due to the lack of such tracking statistics in 2019, we assume that the number of commercial flights and the number of total flights have the same change rate from 2019 to 2020 to estimate the international aviation emissions from total flights in the first quarter in 2019.

For global shipping

The Third IMO GHG Study published global shipping CO_2 emissions from 2007-2012 [30]. And we collected global shipping CO_2 emissions during the period of 2013-2015 from ICCT report [31]. In addition, IEA released international shipping CO_2 emissions from 2000 to 2018 (https://www.iea.org/reports/tracking-transport-2019/international-shipping).

International shipping CO_2 emissions released by IEA were on average 23% lower than those published by IMO. We used this ratio to modify international shipping CO2 emissions from IEA. According to the Third IMO GHG Study, CO_2 emissions from international shipping accounts for 87% of global shipping emissions, domestic and fishing accounts for 9% and 4%, respectively. We estimated global CO2 shipping emissions from 2016-2018 with the modified IEA's international emissions and the ratio between international shipping and global shipping emissions. And we extrapolated emissions from 2007-2018 to estimate emissions in 2019. We obtained emissions for the first quarter of 2019 based on the assumption that monthly variation is flat in shipping CO_2 emissions. In addition, we assume that the change in shipping emissions is linearly related to the change in ship's volume. We collected the change in container ships (https://www.straitstimes.com/business/economy/coronavirus-global-container-shipments-set-to-fall-30-in-next-few-months), bulk carriers ship (http://www.eworldship.com/html/2020/bulk_market_0408/158450.html), Oil Tankers (http://www.eworldship.com/html/2020/ship_market_observation_0415/158673.html) and Other 19 ship class (http://www.msivt.com/news/archive/2020).

3) Satellite observation and data sources:

We obtained monthly NO_2 data from the Ozone Monitoring Instrument (OMI) provided by Tropospheric Emission Monitoring Internet Service (TEMIS), which has with a spatial resolution of 0.125° x 0.125° and a temporal coverage from January 2013 to March 2020. For AOD, we chose daily Level 2 MOD 04 data from MODIS (Levy et al., 2015) and then calculated the monthly averaged AOD f from January 2013 to March 2020. Only "good" and "very good" data (in AOD_550_Dark_Target_Deep_Blue_Combined_QA_Flag 2 and 3) were kept in the calculation. At last, we calculated the monthly XCO2 data with a resolution of 2.5° x 2.5° from the Greenhouse Gases Observing Satellite "IBUKI" (GOSAT). Because of the delay in the data processing at National Institute for Environmental Studies (NIES), we used a bias-uncorrected version V02.81 for the period of January 2013 to March 2020. With the consideration of the focus on an abnormal event due to COVID-19, the bias-uncorrected data is proper for this study.

All of the monthly averaged data were regridded to 1° x 1°. We focused on four regions, China, USA, EU4 (UK, France, Germany, and Italy), and Indian, and then calculated the country level monthly averaged NO_2, AOD, and XCO_2 values. In order to highlight the historical abnormal events, we removed the inter-annual and seasonal variabilities from the monthly averaged country level data. Detrend and deseasonalization can largely reduce the impact of policy relevant changes and accentuate the anomalies in the time series.

Data Availability Statement

All data generated or analyzed during this study are included in this article (and its Data descriptor paper and supplementary information files).

Code Availability Statement

The code generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

References:

1 Myllyvirta, L. Coronavirus temporarily reduced China's CO_2 emissions by a quarter. (2020).

2 Evans, S. Analysis: Coronavirus set to cause largest ever annual fall in CO_2 emissions. (2020).

3 McKibbin, W. J. & Fernando, R. The global macroeconomic impacts of COVID-19: Seven scenarios. (2020).

4 Economics, O. World Economic Prospects Monthly.(4/2020). *Economic Outlook* **44** (2020).

5 Gopinath, G. The Great Lockdown: Worst Economic Downturn Since the Great Depression. (2020).

6 Crippa, M. *et al.* High resolution temporal profiles in the Emissions Database for Global Atmospheric Research. *Scientific Data* **7**, 121, doi:10.1038/s41597-020-0462-2 (2020).

7 International Energy Agency. *CO2 Emissions from Fuel Combustion 2019*. (2019).

8 BP. BP Statistical Review of World Energy 2018. (2018).

9 Janssens-Maenhout, G. *et al.* EDGAR v4. 3.2 Global Atlas of the three major Greenhouse Gas Emissions for the period 1970–2012. *Earth System Science Data* **11**, 959-1002 (2019).

10 Le Quéré, C. *et al.* Global carbon budget 2018. *Earth System Science Data* **10**, 2141-2194 (2018).

11 Olivier, J. G., Schure, K. & Peters, J. Trends in global CO_2 and total greenhouse gas emissions. *PBL Netherlands Environmental Assessment Agency* **5** (2017).

12 Shah, V. *et al.* Effect of changing NO_x lifetime on the seasonality and long-term trends of satellite-observed tropospheric NO_2 columns over China. *Atmos. Chem. Phys.* **20**, 1483-1495, doi:10.5194/acp-20-1483-2020 (2020).

13 Zheng, B. *et al.* Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions. *Atmos. Chem. Phys.* **18**, 14095-14111, doi:10.5194/acp-18-14095-2018 (2018).

14 Spicer, C. W., Kenny, D. V., Ward, G. F. & Billick, I. H. Transformations, lifetimes, and sources of NO_2, HONO, and HNO_3 in indoor environments. *Air & Waste* **43**, 1479-1485 (1993).

15 Myhre, G., Myhre, C., Samset, B. & Storelvmo, T. Aerosols and their relation to global climate and climate sensitivity. *Nature Education Knowledge* **4**, 7 (2013).
16 Forster, P. *et al.* in *Climate Change 2007. The Physical Science Basis* (2007).
17 Zhang, R. *et al.* Formation of urban fine particulate matter. *Chemical reviews* **115**, 3803-3855 (2015).
18 Zhang, F. *et al.* An unexpected catalyst dominates formation and radiative forcing of regional haze. *Proceedings of the National Academy of Sciences* **117**, 3960-3966 (2020).
19 Boersma, K. F. *et al.* Improving algorithms and uncertainty estimates for satellite NO2 retrievals: results from the quality assurance for the essential climate variables (QA4ECV) project. *Atmospheric Measurement Techniques* **11**, 6651-6678 (2018).
20 Sayer, A. M., Hsu, N., Bettenhausen, C. & Jeong, M. J. Validation and uncertainty estimates for MODIS Collection 6 "Deep Blue" aerosol data. *Journal of Geophysical Research: Atmospheres* **118**, 7864-7872 (2013).
21 Watanabe, H. *et al.* Global mapping of greenhouse gases retrieved from GOSAT Level 2 products by using a kriging method. *International Journal of Remote Sensing* **36**, 1509-1528 (2015).
22 Economics, O. World Economic Prospects Monthly.(2/2020). *Economic Outlook* **44**, 1-33 (2020).
23 IEA. *World Energy Balances 2019*. (2019).
24 Friedlingstein, P. *et al.* Global carbon budget 2019. *Earth System Science Data* **11**, 1783-1838 (2019).
25 Guan, D., Liu, Z., Geng, Y., Lindner, S. & Hubacek, K. The gigatonne gap in China's carbon dioxide inventories. *Nature Climate Change* **2**, 672-675 (2012).
26 Marland, G. China's uncertain CO 2 emissions. *Nature Climate Change* **2**, 645-646 (2012).
27 Liu, Z. *et al.* Reduced carbon emission estimates from fossil fuel combustion and cement production in China. *Nature* **524**, 335-338 (2015).
28 Liu, Z., Zheng, B. & Zhang, Q. New dynamics of energy use and CO2 emissions in China. *arXiv preprint arXiv:1811.09475* (2018).
29 The International Council on Clean Transportation. CO2 emissions from commercial aviation. (2019).
30 Smith, T. W. P. *et al.* Third IMO Greenhouse Gas Study 2014. (2015).
31 Olmer, N., Comer, B., Roy, B., Mao, X. & Rutherford, D. Greenhouse gas emissions from global shipping, 2013-2015. (2017).

Supplementary Information

SI Table 1 Sectoral changes in 2020 by countries or regions.

	Countries/Regions	Jan	Feb	Mar	Jan-Mar
Electricity	China	/	/	-4.6%	-6.8%
	India	2.7%	10.4%	-8.7%	1.0%
	US	-6.8%	-1.0%	-6.7%	-4.9%
	Europe (EU27 &UK)	-3.8%	1.2%	-4.5%	-2.5%
	Japan	-1.0%	-4.3%	-1.2%	-3.7%
	Brazil	-3.9%	2.2%	-1.3%	-1.1%
	Russia	-3.4%	0.5%	-2.9%	-2.0%
	Countries/Regions	Jan	Feb	Mar	Jan-Mar
Transport	China	2.6%	-75.1%	-34.2%	-37.2%
	India	0.0%	1.0%	-22.9%	-7.6%
	US	0.0%	4.3%	-10.0%	-2.7%
	Europe (EU27 &UK)	0.0%	3.1%	-22.8%	-7.3%
	Japan	0.0%	-1.2%	-5.3%	-2.0%
	Brazil	0.0%	-0.6%	-20.0%	-6.9%
	Russia	0.0%	0.0%	0.0%	0.0%
	Countries/Regions	Jan	Feb	Mar	Jan-Mar
Industry	China	/	/	-6.9%	-8.1%
	India	-0.4%	3.9%	-22.7%	-7.0%
	US	-1.2%	0.1%	-5.5%	-2.2%
	Europe (EU27 &UK)	-1.6%	-1.6%	-6.4%	-3.2%
	Japan	-2.4%	-5.7%	-17.4%	-8.9%
	Brazil	-0.9%	-0.5%	-5.8%	-2.4%
	Russia	1.1%	3.3%	0.4%	1.6%

SI Table 2. Monthly changes in power sector in the first quarter in 2020 by countries or regions.

Countries/Regions	**Jan**	**Feb**	**Mar**	**Jan-Mar**
China			-4.6%	-6.8%
India	2.7%	10.4%	-8.7%	1.0%
United States	-6.8%	-1.0%	-6.7%	-4.9%
Europe (EU27 & UK)	-3.8%	1.2%	-4.5%	-2.5%
Brazil	-3.9%	2.2%	-1.3%	-1.1%
Japan	-1.0%	-4.3%	-1.2%	-3.7%
Russia	-3.4%	0.5%	-2.9%	-2.0%
European Countries				
Austria	-14.5%	7.7%	-2.2%	-3.7%
Belgium	1.4%	8.2%	-3.6%	1.8%
Bulgaria	-14.1%	-9.0%	-10.6%	-11.3%
Czech Republic	-5.7%	-5.4%	-5.3%	-5.5%
Denmark	2.3%	16.8%	-12.7%	1.5%
Estonia	-62.4%	-48.3%	-43.7%	-53.3%
Finland	-10.1%	0.3%	2.9%	-2.6%
France	-2.0%	1.7%	-4.6%	-1.7%
Germany	-8.6%	0.3%	-8.2%	-5.7%
Greece	-15.9%	-5.1%	-9.0%	-10.7%
Hungary	-4.7%	18.4%	21.3%	9.8%
Italy	-5.7%	-2.5%	-14.5%	-7.6%
Latvia	5.1%	27.7%	-1.6%	8.6%
Lithuania	4.2%	33.1%	-0.3%	11.5%
Netherlands	67.1%	6.9%	-15.1%	13.8%
Poland	-7.2%	1.3%	-5.6%	-4.0%
Portugal	15.8%	15.8%	17.7%	16.4%
Romania	-0.8%	-5.5%	-3.0%	-3.1%
Slovakia	-2.8%	8.3%	-3.1%	0.5%
Slovenia	3.7%	-10.9%	0.7%	-2.3%
Spain	-7.2%	-0.8%	2.2%	-2.2%
Swede	3.5%	5.6%	6.6%	5.2%
United Kingdom	-8.9%	0.0%	-0.9%	-3.6%

SI Table 3. Monthly mobility changes in 2020 by countries or regions.

Countries/Regions	**Jan**	**Feb**	**Mar**	**Jan-Mar**
China	7.4%	-75.1%	-34.2%	-36.2%
India	-	1.0%	-22.9%	-7.6%
United States	-	4.3%	-10.0%	-2.7%
Europe (EU27 & UK)	-	3.1%	-22.8%	-7.3%
Brazil	-	-0.6%	-20.0%	-6.9%
Japan	-	-1.2%	-5.3%	-2.0%
European Countries				
Austria	-	7.9%	-30.1%	-9.0%
Belgium	-	-1.3%	-25.8%	-9.0%
Bulgaria	-	6.1%	-23.9%	-7.1%
Croatia	-	4.8%	-24.3%	-7.5%
Czechia	-	5.0%	-20.8%	-6.3%
Denmark	-	-0.3%	-10.7%	-3.7%
Estonia	-	1.3%	-12.9%	-4.2%
Finland	-	1.5%	-11.5%	-3.7%
France	-	2.1%	-34.9%	-11.5%
Germany	-	1.9%	-14.1%	-4.5%
Greece	-	4.9%	-27.2%	-8.5%
Hungary	-	7.9%	-16.0%	-4.1%
Ireland	-	-1.6%	-19.8%	-7.0%
Italy	-	1.3%	-51.5%	-17.3%
Latvia	-	1.7%	-8.7%	-2.7%
Lithuania	-	2.5%	-15.1%	-4.7%
Luxembourg	-	-1.3%	-28.7%	-10.0%
Malta	-	11.3%	-24.7%	-6.5%
Netherlands	-	-0.9%	-14.9%	-5.2%
Poland	-	2.8%	-23.1%	-7.4%
Portugal	-	6.5%	-31.8%	-9.8%
Romania	-	4.2%	-23.5%	-7.3%
Slovakia	-	6.1%	-27.1%	-8.2%
Slovenia	-	4.3%	-30.5%	-9.7%
Spain	-	5.7%	-40.8%	-13.0%
Sweden	-	0.8%	-6.3%	-2.0%
United Kingdom	-	-2.1%	-17.0%	-6.1%

SI Table 4. Growth rates of industrial sector comparing to the same periods of last year in 2020.

Countries/Regions	Jan	Feb	Mar	Jan-Mar
China			-6.9%	-8.1%
India	-0.4%	3.9%	-22.7%	-7.0%
US	-1.2%	0.1%	-5.5%	-2.2%
Europe (EU27 & UK)	-1.6%	-1.6%	-6.4%	-3.2%
Japan	-2.4%	-5.7%	-17.4%	-8.9%
Brazil	-0.9%	-0.5%	-5.8%	-2.4%
Russia	1.1%	3.3%	0.4%	1.6%