A novel method to estimate emissions reductions of mobility restriction: the case of the COVID-19 pandemic

SUPPLEMENTARY INFORMATION

Authors:

Francesco Pomponi*, Mengyu Li, Ya-Yen Sun, Arunima Malik, Manfred Lenzen, Grigorias Fountas, Bernardino D’Amico, Ortzi Akizu-Gardoki, Maria Luque Anguita

1 Resource Efficient Built Environment Lab (REBEL), Edinburgh Napier University, EH10 5DT Edinburgh UK
2 ISA, School of Physics A28, The University of Sydney, NSW 2006, Australia
3 Business School, The University of Queensland, QLD, 4067, Australia
4 Discipline of Accounting, School of Business, The University of Sydney, NSW - 2006
5 Transport Research Institute (TRI), School of Engineering and the Built Environment, Edinburgh Napier University
6 Faculty of Engineering of Bilbao, University of the Basque Country (UPV/EHU), 48013 Bilbao Spain
7 School of Computing, Edinburgh Napier University, EH10 5DT Edinburgh UK

*Corresponding author: f.pomponi@napier.ac.uk - +447708378100
SI1 – MRIO Data

The Global MRIO Lab\(^1\) was used to compile MRIO data \((\mathbf{x}, \mathbf{T}, \mathbf{y}, \mathbf{A}, \mathbf{y}_S)\) for 38 regions, each with 26 sectors (SI1). These data were generated by reconciling and balancing several global data sources, such as the UN’s Main Aggregates\(^2\), Official Country Accounts\(^3\), and Comtrade\(^4\) databases. These data are available up to the year 2018. To simulate the world economy for the year 2020, we used country-specific GDP growth rates\(^5\) to project the 2018 global MRIO table to 2020, and then re-balanced using the KRAS method\(^6\). Satellite accounts are based on global data emissions of greenhouse gases\(^7\), PM\(_{2.5}\) and air pollutants\(^8\). For the satellite accounts, we decided to base our assessment on the latest version of EDGAR (v5.0) – updated up to year 2018. In the absence of a robust data source for projecting the 2018 emissions data-set to 2020, we have assumed the global emissions sectoral and regional profile to be the same for year 2020.

The regions covered in the MRIO table created for this study, and the sectors covered for each of them, are shown in Table S1.

| MRIO Countries/Regions | MRIO Sectors |
|------------------------|--------------|
| 1 Australia            | 1 Agriculture|
| 2 Brazil               | 2 Forestry, wood, paper |
| 3 Canada               | 3 Fishing |
| 4 China                | 4 Mining |
| 5 France               | 5 Food products |
| 6 Germany              | 6 Solid fuels |
| 7 Hong Kong            | 7 Liquid fuels |
| 8 India                | 8 Gaseous fuels |
| 9 Indonesia            | 9 Chemicals & plastics |
| 10 Iran                | 10 Textiles & leather products |
| 11 Italy               | 11 Metal products |
| 12 Japan               | 12 Equipment |
| 13 Malaysia            | 13 Ceramic & other manufacturing |
| 14 Mexico              | 14 Construction |
| 15 Middle East         | 15 Electricity generation |
| 16 Nigeria             | 16 Gas supply |
| 17 Rest of Africa      | 17 Air transport |
| 18 Rest of Central America | 18 Other transport & storage |
| 19 Rest of East Asia   | 19 Tourism & hospitality |
| 20 Rest of EU          | 20 Retail & wholesale trade |
| 21 Rest of Europe      | 21 Education |
| 22 Rest of FSU         | 22 Finance & insurance |
| 23 Rest of Oceania     | 23 Business services |
| 24 Rest of OPEC        | 24 Public services |
| 25 Rest of South America | 25 Health care |
| 26 Rest of South Asia  | 26 Private services |
| 27 Rest of South East Asia |             |
| 28 Russia              |             |
The rationale for the choice of the regional classification is to capture countries and regions most severely hit by the COVID-19 pandemic at the time of analysis as well as key players in the global economy. Even if Russia, China and Iran are not covered by the Google Community Mobility Reports (CMRs) they are instead covered in our MRIO table to ensure that spillover effects occurring in those countries would be captured by our model. The regional details of the 38 regions covered is shown in Figure S1.

Google Community Mobility Reports (CMR) were initially released in PDF format and subsequently made available as a global CSV file. By definition Google covers ‘community’ travel therefore inter-regional transportation and international travel is excluded. The mobility
change is measured against a baseline (the 5-week period Jan 3–Feb 6, 2020) and data starts from 15th Feb 2020 and Google typically releases a new batch of data every few days. Of course there have been mobility changes also in the baseline weeks and Google itself acknowledge the difficulty in picking the ‘perfect’ baseline. What is worth considering for the scope of our analysis is that (i) those five weeks were a moment in 2020 where China was nearly solely largely affected by the pandemic (and we do not cover China since it is unavailable in the CMRs) and (ii) that the rest of the countries we cover were not (Italy for instance, was carrying on largely as normal in those five weeks and it has been the first country other than China to implement movement-controlling measures in early March). The day of the release does not match the latest day for which data is available in that release due to the time it takes to process global mobility data. This lag is generally of around 4-5 days. For this paper we used data released on 3rd June 2020 offering data up until 29th May 2020. Google data is by nature aggregated and therefore a ‘correct’ allocation is unlikely to exist. We overcome this by developing 12 scenarios (see Figure 1 in the main paper), which are further differentiated by 2 different allocation approaches to assign national data to countries which belong to larger regions in our MRIO table. This different allocation affects a large number of the countries covered since only 22 (out of 129) are modelled individually in our MRIO table. The remainder belongs to various world regions as shown in SI1. Arguably, two main approaches are possible:

1. Use Gross Domestic Product (GDP) of a country in relation to the GDP of the region it belongs to as a weight to assign a country’s share to the region; this well represents the economy of that country in relation to the economy of the region
2. Use the population of a country in relation the population of the region as a weight; this represents well the people of that country since Google data reports on the movement of people.

The relevance of this different attribution can be seen by few exemplary countries. For instance, Switzerland (part of the Rest of Europe region) has a weight of 0.86 in terms of GDP but only of 0.30 in terms of population. Similarly, New Zealand’s weights within the Rest of Oceania region are 0.79 and 0.26, respectively.

Interpretation is required to assign percent reductions available from Google to the different sectors in our MRIO model. To limit the uncertainty arising from interpretation we develop 12 scenarios (Figure 1 in the manuscript). These span from assigning different ranges of consumption losses due to fewer visits (e.g. 10% reduction in mobility to retail outlets in a country turns into 0%, 5%, and 10% reduction in the MRIO retail sector for that specific country as Figure 1 shows) as well as different ranges of transport reductions. These latter are further differentiated between private car use vs. public transport, and reduced fuel usage for fewer car trips is weighted against the share of cars vs. total vehicles in each of the countries covered. Further, we assess the validity of Google data by comparing it against Apple Mobility Trends Reports (SI2). By finding good correspondence between Google and Apple data we can establish that Android users’ behaviour—which is a large subset of the global population—can be considered a representative sample of the whole global population. The attribution is based on a correspondence table (Table S2) that resulted from extensive discussion within the research team on how to interpret Google’s definition of the different categories with the sectoral disaggregation in our MRIO table. For instance, for scenario S1 (please see Figure 1)—which indicates a full correspondence between mobility restriction and reduced consumption—we would translate a 30% reduction in Google mobility data into a 30% reduction in the sectors that we have matched with Google’s ‘Retail & recreation’ and ‘Grocery & Pharmacy’. To test the sensitivity of our results to such assumptions we also have scenarios (e.g. S4, S8) where
only a partial correspondence (half) is considered between mobility and consumption as well as scenarios where no correspondence exists (i.e. reduced mobility does not reduce consumption) such as scenarios S5 and S10 for instance.

Table S2 - base attribution between Google CMRs and sectors in our MRIO table

| Google CMRs category | Description by Google                                                                 | Corresponding MRIO sectors                  |
|----------------------|----------------------------------------------------------------------------------------|---------------------------------------------|
| Retail & recreation  | Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. | Retail & wholesale trade, Tourism & hospitality, Private services |
| Grocery & Pharmacy   | Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies. | Retail & wholesale trade, Food products, Chemicals & plastics |
| Parks                | Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens. | Public services |
| Transit stations     | Mobility trends for places like public transport hubs such as subway, bus, and train stations. | Other transport & storage |
| Workplaces           | Mobility trends for places of work.                                                    | Electricity generation, Gas supply           |
| Residential          | Mobility trends for places of residence.                                               | Electricity generation, Gas supply           |
| N/A                  |                                                                                         | Liquid fuels                                |

It should be noted that Google does not have a category to capture reduced visits, say, to petrol stations. Yet, reduced fuel usage is a key component of the environmental gains arising from the mobility restriction caused by the pandemic. To capture these in the sector ‘liquid fuels’ for each country \(i\) of the 129 we cover in our MRIO table we adopted the following formula:

\[
LF_{\%i} = \alpha_i \cdot \beta_i \cdot \max \{Retail_{\%i}, Workplace_{\%i}\}
\]

where: \(\alpha_i\) is a value between 0 and 1 representing the car modal share for that country (to account for the part of the population that moves with private cars and not public transport); \(\beta_i\) is a value between 0 and 1 representing the share of cars over total vehicles for that country (to account for vans, buses and trucks which might still be running during the pandemic); and \(Retail_{\%i}\) and \(Workplaces_{\%i}\) are the percent reduction values reported by Google for those two sectors for the country \(i\). This likely represents an underestimate, hence a conservative assumption, because surely also fewer vans, buses and trucks are running during the pandemic. The values of \(\alpha_i, \beta_i\) are taken from a newly developed dataset with global coverage. Exact values of the two coefficients used for each country in this analysis are given in SI3.

**Apple vs. Google comparison**

Similarly to Google, Apple is also helping global efforts to monitor and manage the covid-19 pandemic through its Maps Mobility Trends Reports. The two datasets are however quite fundamentally different: while Google reports the average reduction of frequency of visits and length of stays in certain places, Apple reports reductions of requests for directions in Apple Maps. In other words, Google data means that someone has either been for a shorter time or not been at all to a place whereas Apple data means that someone simply has not searched for
directions to go to a place. For this Apple data is less representative of reduced mobility, for many commuters might not look for directions to their places of work and would therefore not be captured by Apple whereas Google would record the lack of commute. However, both datasets are built on an extremely large number of datapoints (Google’s Android has 70.68% of the mobile operating system global market share, and iOS has 28.79% - thus covering 99.47% of smartphone users globally) and comparing their trends might be useful to cautiously confirm the possibility of considering Google data as representative of the global population. Due to the different countries covered in the two datasets, we analysed their trends at continent level and this this is shown in Figure S2.

As said, the two datasets are different in scope, and in the data they represent. Yet, it is remarkable how aligned the two trends are. Reductions from Apple data are consistently greater than from Google data and in some cases are close to -100%. This is however expected since Apple records reduced requests for direction in Maps. If people are in lockdown and movement is forbidden, they will surely heavily reduce their need for directions. Given the close match of the trends between Apple and Google data and the fact that together they represent nearly the totality of smartphone users globally, we believe our assumption to utilise Google data as a proxy for the whole global population is realistic and justified. Good agreement between Google and Apple data has also been observed in other recent studies, for instance in modelling and projecting the impact of Covid-19 on US motor gasoline demand. It should be noted that Apple data is available for Russia, one of the countries not covered by Google. One might therefore think of extracting Apple data for Russia and use it in our analysis. However, Apple only offers one omni-comprehensive value for reduced direction request in Maps vs. the six different place categories offered by Google. Our Apple/Google comparison was possible because we averaged Google data and compared it to the single value offered by Apple but the opposite (i.e. starting from the single value offered by Apple to unpack it into six meaningful values) is not possible. For this reason Russia remains excluded from our analysis even if Apple data exists for it.
Figure S2 – Comparison of trends at continent level between Apple Mobility Reports (dashed lines) and Google Mobility Reports (solid lines). Apple data starts from January 13, but to enable a comparison with Google data, we have used the time period 13/01-14/02 to develop a baseline (similarly to what Google does for the five weeks prior to February 15 when its Mobility Reports commence).

SI3 – Transport data

Table S3 - Values of $\alpha_i$,$\beta_i$ for all countries considered in this analysis

| ISO ALPHA 2 | Short name                  | Modal share | Vehicle Share |
|-------------|-----------------------------|-------------|---------------|
|             |                             | Public transport | Car [$\alpha_i$] | Other vehicles | Car [$\beta_i$] |
| AW          | Aruba                       | 27.21%      | 72.79%        | 33.35%        | 66.65%        |
| AF          | Afghanistan                 | 67.60%      | 32.40%        | 47.27%        | 52.73%        |
| AO          | Angola                      | 41.46%      | 58.54%        | 56.02%        | 43.98%        |
| AE          | United Arab Emirates        | 14.00%      | 86.00%        | 10.65%        | 89.35%        |
| AR          | Argentina                   | 43.00%      | 57.00%        | 24.19%        | 75.81%        |
| AG          | Antigua and Barbuda         | 31.17%      | 68.83%        | 33.36%        | 66.64%        |
| AU          | Australia                   | 12.00%      | 88.00%        | 22.52%        | 77.48%        |
| AT          | Austria                     | 33.05%      | 66.95%        | 8.81%         | 91.19%        |
| BE          | Belgium                     | 18.28%      | 81.72%        | 10.24%        | 89.76%        |
| BJ          | Benin                       | 27.00%      | 73.00%        | 21.14%        | 78.86%        |
| BF          | Burkina Faso                | 28.00%      | 72.00%        | 47.14%        | 52.86%        |
| BD          | Bangladesh                  | 71.10%      | 28.90%        | 44.74%        | 55.26%        |
| BG          | Bulgaria                    | 15.20%      | 84.80%        | 19.00%        | 81.00%        |
| BH          | Bahrain                     | 13.00%      | 87.00%        | 13.64%        | 86.36%        |
| BS          | Bahamas                     | 26.00%      | 74.00%        | 45.50%        | 54.50%        |
| ISO ALpha 2 | Short name          | Modal share | Vehicle Share |
|------------|---------------------|-------------|---------------|
|            |                     | Public transport | Car [%] | Other vehicles | Car [%] |
| BA         | Bosnia and Herzegovina | 29.70% | 70.30% | 37.70% | 62.30% |
| BY         | Belarus             | 80.00% | 20.00% | 21.57% | 78.43% |
| BZ         | Belize              | 39.95% | 60.05% | 28.63% | 71.37% |
| BO         | Bolivia             | 81.50% | 16.50% | 71.21% | 28.79% |
| BR         | Brazil              | 39.81% | 60.19% | 26.51% | 73.49% |
| BB         | Barbados            | 30.23% | 69.77% | 2.62%  | 97.38% |
| BW         | Botswana            | 35.42% | 64.58% | 52.60% | 47.40% |
| CA         | Canada              | 3.35%  | 96.65% | 26.20% | 73.80% |
| CH         | Switzerland         | 22.75% | 77.25% | 15.99% | 84.01% |
| CL         | Chile               | 47.80% | 52.20% | 41.11% | 58.89% |
| CI         | Côte d'Ivoire       | 37.96% | 62.04% | 60.98% | 39.02% |
| CM         | Cameroon            | 47.44% | 52.56% | 30.58% | 69.42% |
| CO         | Colombia            | 51.04% | 48.96% | 49.81% | 50.19% |
| CV         | Cabo Verde          | 41.03% | 58.97% | 27.72% | 72.28% |
| CR         | Costa Rica          | 33.90% | 66.10% | 33.59% | 66.41% |
| CZ         | Czech Republic      | 21.41% | 78.59% | 18.89% | 81.11% |
| DE         | Germany             | 15.77% | 84.23% | 9.16%  | 90.84% |
| DK         | Denmark             | 17.93% | 82.07% | 16.28% | 83.72% |
| DO         | Dominican Republic  | 35.99% | 64.01% | 46.29% | 53.71% |
| EC         | Ecuador             | 74.31% | 25.69% | 66.16% | 33.84% |
| EG         | Egypt               | 34.00% | 66.00% | 46.89% | 53.11% |
| ES         | Spain               | 18.41% | 81.59% | 21.21% | 78.79% |
| EE         | Estonia             | 19.50% | 80.50% | 23.14% | 76.86% |
| FI         | Finland             | 15.80% | 84.20% | 7.50%  | 92.50% |
| FJ         | Fiji                | 39.16% | 60.84% | 37.05% | 62.95% |
| FR         | France              | 18.02% | 81.98% | 12.05% | 87.95% |
| GA         | Gabon               | 34.26% | 65.74% | 49.21% | 50.79% |
| GB         | United Kingdom      | 14.64% | 85.36% | 12.49% | 87.51% |
| GE         | Georgia             | 32.80% | 67.20% | 39.50% | 60.50% |
| GH         | Ghana               | 78.00% | 22.00% | 40.61% | 59.39% |
| GW         | Guinea-Bissau       | 53.78% | 46.22% | 18.18% | 81.82% |
| GR         | Greece              | 18.12% | 81.88% | 9.08%  | 90.92% |
| GT         | Guatemala           | 23.00% | 77.00% | 66.00% | 34.00% |
| HK         | Hong Kong           | 93.00% | 7.00%  | 30.99% | 69.01% |
| HN         | Honduras            | 44.70% | 55.30% | 75.00% | 25.00% |
| HR         | Croatia             | 15.70% | 84.30% | 11.37% | 88.63% |
| HT         | Haiti               | 52.55% | 47.45% | 50.00% | 50.00% |
| HU         | Hungary             | 18.02% | 81.98% | 16.88% | 83.12% |
| ID         | Indonesia           | 36.00% | 64.00% | 51.63% | 48.37% |
| IN         | India               | 57.70% | 42.30% | 53.87% | 46.13% |
| IE         | Ireland             | 17.40% | 82.60% | 9.58%  | 90.42% |
| IQ         | Iraq                | 37.79% | 62.21% | 68.49% | 31.51% |
| IL         | Israel              | 14.30% | 85.70% | 22.27% | 77.73% |
| IT         | Italy               | 18.02% | 81.98% | 9.95%  | 90.05% |
| JM         | Jamaica             | 39.02% | 60.98% | 21.05% | 78.95% |
| JO         | Jordan              | 33.00% | 67.00% | 9.78%  | 90.22% |
| JP         | Japan               | 36.76% | 63.24% | 24.43% | 75.57% |
| KZ         | Kazakhstan          | 60.00% | 40.00% | 20.32% | 79.68% |
| KE         | Kenya               | 49.24% | 50.76% | 48.67% | 51.33% |
| ISO ALPHA 2 | Short name      | Modal share | Vehicle Share |
|------------|----------------|-------------|---------------|
|            |                | Public transport | Car [%] | Other vehicles | Car [%] |
| KG         | Kyrgyzstan     | 64.30%       | 35.70%       | 59.19%         | 40.81%   |
| KH         | Cambodia       | 49.31%       | 50.69%       | 14.29%         | 85.71%   |
| KR         | Republic of Korea | 40.95%     | 59.05%       | 32.28%         | 67.72%   |
| KW         | Kuwait         | 24.98%       | 75.02%       | 11.00%         | 89.00%   |
| LA         | Laos           | 46.43%       | 53.57%       | 90.00%         | 10.00%   |
| LB         | Lebanon        | 12.70%       | 87.30%       | 16.54%         | 83.46%   |
| LY         | Libya          | 36.14%       | 63.86%       | 40.87%         | 59.13%   |
| LI         | Liechtenstein  | 17.20%       | 82.80%       | 2.93%          | 97.07%   |
| HK         | Sri Lanka      | 51.50%       | 48.50%       | 65.55%         | 34.45%   |
| LT         | Lithuania      | 9.20%        | 90.80%       | 7.09%          | 92.91%   |
| LU         | Luxembourg     | 17.10%       | 82.90%       | 7.09%          | 92.91%   |
| LV         | Latvia         | 17.30%       | 82.70%       | 19.73%         | 80.27%   |
| MD         | Republic of Moldova | 19.72%   | 80.28%       | 35.00%         | 65.00%   |
| MX         | Mexico         | 60.00%       | 40.00%       | 32.92%         | 67.08%   |
| MK         | North Macedonia| 19.64%       | 80.36%       | 25.13%         | 74.87%   |
| ML         | Mali           | 52.19%       | 47.81%       | 26.31%         | 73.69%   |
| MT         | Malta          | 17.71%       | 82.29%       | 15.30%         | 84.70%   |
| MM         | Myanmar        | 47.37%       | 52.63%       | 47.62%         | 52.38%   |
| MN         | Mongolia       | 40.31%       | 59.69%       | 32.39%         | 67.61%   |
| MZ         | Mozambique     | 79.67%       | 20.33%       | 32.62%         | 67.38%   |
| MU         | Mauritius      | 33.54%       | 66.46%       | 25.12%         | 74.88%   |
| MY         | Malaysia       | 25.00%       | 75.00%       | 20.21%         | 79.79%   |
| NE         | Niger          | 56.94%       | 43.06%       | 13.00%         | 87.00%   |
| NG         | Nigeria        | 45.10%       | 54.90%       | 8.25%          | 91.75%   |
| NI         | Nicaragua      | 45.42%       | 54.58%       | 77.67%         | 22.33%   |
| NL         | Netherlands    | 17.65%       | 82.35%       | 10.60%         | 89.40%   |
| NO         | Norway         | 15.18%       | 84.82%       | 16.47%         | 83.53%   |
| NP         | Nepal          | 47.80%       | 52.20%       | 26.80%         | 73.20%   |
| NZ         | New Zealand    | 3.44%        | 96.56%       | 24.75%         | 75.25%   |
| OM         | Oman           | 28.50%       | 71.50%       | 25.02%         | 74.98%   |
| PK         | Pakistan       | 57.20%       | 42.80%       | 19.18%         | 80.82%   |
| PA         | Panama         | 73.50%       | 26.50%       | 33.93%         | 66.07%   |
| PE         | Peru           | 62.00%       | 38.00%       | 42.24%         | 57.76%   |
| PH         | Philippines    | 59.23%       | 40.77%       | 55.48%         | 44.52%   |
| PG         | Papua New Guinea| 43.70%     | 56.30%       | 53.85%         | 46.15%   |
| PL         | Poland         | 15.86%       | 84.14%       | 22.22%         | 77.78%   |
| PR         | Puerto Rico    | 26.34%       | 73.66%       | 20.35%         | 79.65%   |
| PT         | Portugal       | 15.00%       | 85.00%       | 11.29%         | 88.71%   |
| PY         | Paraguay       | 38.30%       | 61.70%       | 61.41%         | 38.59%   |
| QA         | Qatar          | 20.37%       | 79.63%       | 25.47%         | 74.53%   |
| RO         | Romania        | 19.70%       | 80.30%       | 34.94%         | 65.06%   |
| RW         | Rwanda         | 52.05%       | 47.95%       | 67.60%         | 32.40%   |
| SA         | Saudi Arabia   | 17.00%       | 83.00%       | 33.44%         | 66.56%   |
| SN         | Senegal        | 47.37%       | 52.63%       | 57.15%         | 42.85%   |
| SG         | Singapore      | 57.62%       | 42.38%       | 24.12%         | 75.88%   |
| SV         | El Salvador    | 41.39%       | 58.61%       | 6.54%          | 93.46%   |
| SK         | Slovakia       | 26.30%       | 73.70%       | 22.94%         | 77.06%   |
| SI         | Slovenia       | 13.49%       | 86.51%       | 7.02%          | 92.98%   |
| SE         | Sweden         | 17.48%       | 82.52%       | 9.82%          | 90.18%   |
| ISO ALPHA 2 | Short name          | Modal share | Vehicle Share |
|-------------|---------------------|-------------|---------------|
|             |                     | Public transport | Car $[\alpha_i]$ | Other vehicles | Car $[\beta_i]$ |
| TG          | Togo                | 53.27%       | 46.73%        | 71.49%         | 28.51%         |
| TH          | Thailand            | 30.00%       | 70.00%        | 62.87%         | 37.13%         |
| TJ          | Tajikistan          | 75.98%       | 24.02%        | 23.68%         | 76.32%         |
| TT          | Trinidad and Tobago | 30.66%       | 69.34%        | 11.84%         | 88.16%         |
| TR          | Turkey              | 29.70%       | 70.30%        | 36.09%         | 63.91%         |
| TW          | Taiwan              | 18.20%       | 81.80%        | 14.37%         | 85.63%         |
| TZ          | Tanzania            | 50.75%       | 49.25%        | 40.85%         | 59.15%         |
| UG          | Uganda              | 52.91%       | 47.09%        | 74.04%         | 25.96%         |
| UY          | Uruguay             | 45.00%       | 55.00%        | 28.11%         | 71.89%         |
| US          | USA                 | 9.42%        | 90.58%        | 50.57%         | 49.43%         |
| VE          | Venezuela           | 56.64%       | 43.36%        | 24.20%         | 75.80%         |
| VN          | Viet Nam            | 14.00%       | 86.00%        | 31.60%         | 68.40%         |
| YE          | Yemen               | 52.77%       | 47.23%        | 51.17%         | 48.83%         |
| ZA          | South Africa        | 38.73%       | 61.27%        | 35.19%         | 64.81%         |
| ZM          | Zambia              | 62.50%       | 37.50%        | 39.80%         | 60.20%         |
| ZW          | Zimbabwe            | 48.59%       | 51.41%        | 11.70%         | 88.30%         |
Figure S1 – Full results in Mt reduction for GHG (a), PM$_{2.5}$ (b), SO$_2$ (c), and NO$_x$ (d).
Figure S2 - Product layer decomposition clustered by key sectors for Scenario 11 (a) and Scenario 12 (b), which correspond to maximum and minimum variations with an attribution based on GDP.
Figure S3 - Product layer decomposition clustered by key sectors for Scenario 23 (a) and Scenario 24 (b), which correspond to maximum and minimum variations with an attribution based on population.
Figure S6 - Product layer decomposition clustered by key regions for Scenario 11 (a) and Scenario 12 (b), which correspond to maximum and minimum variations with an attribution based on GDP.
Figure S7 - Product layer decomposition clustered by key regions for Scenario 23 (a) and Scenario 24 (b), which correspond to maximum and minimum variations with an attribution based on population.
SI5 – Uncertainty and limitations

This research deals with determining emissions reduction caused by global mobility constraint as measured by Google as a response to the COVID-19 pandemic through scenario modelling combined with the disaster analysis method by Steenge and Bočkarjova and transport data on modal share and car share for 129 countries, and then applied to a global setting described by a global MRIO database. There are limitations and uncertainties involved with any research; in our case, they are three-fold:

5.1 MRIO-related

This same method was applied for quantifying the uncertainties in the assessment of the carbon footprint of global tourism and a detailed explanation of the uncertainty on the method can be found in the work by Lenzen and colleagues. Specifically, our MRIO-related uncertainty analysis captures the following stochastic variations: 1) Raw data; 2) Building the MRIO Table using KRAS method; 3) Multipliers; 4) Footprint Components (e.g., final demand). By estimating the standard deviations of the aforementioned four variations sources, we determine the stochastic variation of the whole MRIO system using Monte Carlo techniques. Results of uncertainty analysis run specifically for this research are shown in Figure S8.
Figure S8 - Results of uncertainty analysis performed through Monte Carlo, stochastic approaches on four scenarios: S11, max values, attribution by GDP (a), S12, min values, attribution by GDP (b), S23, max values, attribution by population (c), and S24, min values, attribution by population (d).

Also, as with every input-output analysis, this study is affected by the known and accepted limitations of the input-output method, namely (1) it is static (does not incorporate price effects of shortages, that in turn regulate demand, and eventually lead to a post-disaster equilibrium), (2) it assumes a fixed production recipe (the coefficients of the input-output technology matrix $A$ are assumed to be constant), and (3) it assumes sector-specific homogeneity.

5.2 Google-related

Data in the CMRs is aggregated by definition and this causes uncertainty on what it actually represents. We have attempted to reduce this uncertainty through a substantial number of scenarios covering a broad range of potential interpretation of the Google data and by comparing Google data with Apple data at continent level to confirm that the behaviour and movement of Android users can be considered representative of the global population. Additionally, Google offers data for 129 global countries, which do not represent the whole world. While they account for a large share of global GDP and global population, the lack of data on China and Russia is a further limitation to the comprehensiveness of our results. Once again, it should be noted though that while direct (and therefore also indirect effects) of mobility restriction in China and Russia are not captured, the indirect effects occurring in China and Russia due to mobility restriction in other countries are instead covered through the IO calculus. Also, the sectors we use to attribute losses in Table S2 are broad sectors and therefore some allocations of loss may cover sub-sectors that are not affected by any losses and in other instances we have not allocated losses where there were some in reality. Such in- and exclusions are likely to sway results in opposite directions, and ultimately lead to uncertainties in the sectoral breakdowns of our results. More generally, such circumstances point to a fundamental problem in economic analyses, such as CGE modelling and all input-output modelling: sector aggregation. Whilst sector aggregation can in principle be overcome by disaggregating the databases underlying the modelling exercise, there are limits to how far this can be taken. These limits are primarily posed by the availability of information, and this is especially true for global analyses that include developing countries. They are to a lesser extent also due to limitations of computer memory. The largest MRIO databases to date distinguish about 15,000 region-sector pairs, and such databases require significant memory and runtime to be handled during compilation and matrix inversion operations.

5.3 Transport-related

Global institutions for integrated ground transport do not exist, contrarily to air and maritime transport for instance. This causes the lack of global and harmonised datasets. While these exist for, for instance, OECD countries or the EU, it is likely that data is collected differently and might be slightly different in what it represents too. We compiled a novel dataset that attempts to overcome these limitations by using different data sources, considering consistent travel modes for data collection, investigating discrepancies, and doing regression and correlation analyses to validate the approach used. Yet, uncertainty remains on whether national data that we retrieved is collected in the same way, and aims to represent the same information, of – say – OECD harmonised transport data. This represents another limitation of our work. In addition, MRIO data on public transport are aggregated across different modes of travel (e.g. train and buses). This represents a further transport-related limitation due to the nature of MRIO data.
SI6 – Statistical analysis

We observed differences in absolute and percentage emissions reductions against the stringency index across the countries and regions we cover (Figure S9).

Figure S9 – Absolute (right) and percentage values (left) of emissions reductions (y-axis) for all 38 countries and regions considered against the Oxford Stringency Index (x-axis, data date: 29/05/2020 which corresponds to the same date the Google CMRs refer to). Both emissions reduction values and stringency indices are normalised between 0 and 1.

For this reason, we explored the significance of the stringency index on the estimated emissions reductions. To do so, we built 34 different linear regression models using a weighted least squares approach (WLS) with varying weights (Table S4) in the software NLOGIT. In addition to GDP and population (and their log) we also explored three additional potential weights as follows:

1. \( ngoogle = \text{number of mobile phones in use in each country} \times 0.7413 \) (74.13% is a global average representing the Android share of all mobile operating systems)
2. \( \text{coverage} = \frac{\text{number of mobile phones}}{100 \text{ citizens}} \)
3. \( w = ngoogle \times \text{coverage} \)

We also incorporated in our models the White estimator\(^{18}\), which corrects the covariance matrix of the model to make it more robust in cases of heteroscedastic estimations – this is in line with NLOGIT recommendations and previous research. White estimator does not change the coefficients of the covariates, but it mainly modifies the standard errors to tackle possible heteroscedasticity issues. Additionally, for each model we performed the Breusch and Pagan test, which has been widely used to identify heteroscedasticity in regression models. This is a chi-square test with a null hypothesis that there is homoscedasticity in the model. For all four best models, the p-value for the Breusch – Pagan test is significantly higher than 0.05, which means that we cannot reject the null hypothesis that there is homoscedasticity in the model considering a 95% level of confidence or higher.

It should be noted that the estimation of these linear regression models can provide some initial, empirical insights into the effect of the stringency of mobility policies on the anticipated emission reductions. To address possible bias in model estimation stemming from unobserved
or spatial heterogeneity, future research can investigate the spatial transferability of the aforementioned effect through the estimation of separate models per geographical region (e.g., Europe, North America and so on). However, spatial analyses require the availability of richer datasets, which go beyond the emission reductions and the stringency index. Availability of an extensive array of country-specific independent variables is important in order to enable multivariate analyses that can capture spatial effects and potentially result in greater explanatory power and statistical performance 19, 20.

Table S4 – Overview of key results for all the statistical models considered to establish the significance of the Stringency Index (S.I.) on our estimates of emissions reductions. In the table log always means log_{10}. Best models are highlighted in green.

| Dependent | Independent | Weighting       | Significance of S.I. | P-value | R² | Breusch-Pagan test |
|-----------|-------------|-----------------|----------------------|---------|----|-------------------|
| log(GHG)  | log(S.I.)   | GDP             | >99%                 | <0.01   | 0.20225 | >0.05             |
| log(GHG)  | log(S.I.)   | population      | >95%                 | <0.05   | 0.19733 | >0.05             |
| log(GHG)  | log(S.I.)   | sqrt (ngoogle)  | >95%                 | <0.05   | 0.15348 | >0.05             |
| log(GHG)  | log(S.I.)   | ngoogle         | >99%                 | <0.01   | 0.18236 | >0.05             |
| log(GHG)  | Stringency  | coverage        | >95%                 | <0.05   | 0.18469 | >0.05             |
| log(GHG)  | Stringency  | coverage        | <90%                 | <0.10   | 0.10633 | >0.05             |
| log(GHG)  | Stringency  | sqrt(covariance) | >95%                | <0.05   | 0.12633 | >0.05             |
| log(GHG)  | log(S.I.)   | w               | None                 | >0.10   | 0.18471 | 0.00              |
| log(GHG)  | S.I.        | w               | None                 | >0.10   | 0.17815 | 0.00              |
| log(GHG)  | log(S.I.)   | sqrt(w)         | None                 | >0.10   | 0.01991 | 0.02              |
| log(PM_{2.5}) | S.I.      | GDP             | None                 | >0.10   | 0.03345 | >0.05             |
| log(PM_{2.5}) | log(S.I)   | GDP             | None                 | >0.10   | 0.05389 | >0.05             |
| PM_{2.5}  | S.I.        | GDP             | None                 | >0.10   | 0.00406 | >0.05             |
| log(PM_{2.5}) | log(S.I)   | population      | >99%                 | <0.01   | 0.13338 | >0.05             |
| log(PM_{2.5}) | log(S.I)   | sqrt(population) | >90%                | <0.10   | 0.08367 | >0.05             |
| log(PM_{2.5}) | log(S.I)   | ngoogle         | >95%                 | <0.05   | 0.1203  | >0.05             |
| log(PM_{2.5}) | log(S.I)   | coverage        | None                 | >0.10   | 0.04788 | >0.05             |
| log(PM_{2.5}) | log(S.I)   | w               | None                 | >0.10   | 0.11336 | 0.00              |
| log(SO_{2}) | log(S.I)   | GDP             | None                 | >0.10   | 0.05989 | >0.05             |
| SO_{2}    | S.I.        | GDP             | None                 | >0.10   | 0.00649 | >0.05             |
| log(SO_{2}) | S.I.        | GDP             | None                 | >0.10   | 0.04382 | >0.05             |
| log(SO_{2}) | log(S.I)   | population      | >95%                 | <0.05   | 0.10384 | >0.05             |
| log (SO_{2}) | log(S.I)   | sqrt(population) | None                | >0.10   | 0.07179 | >0.05             |
| log (SO_{2}) | log(S.I)   | ngoogle         | >95%                 | 0.05    | 0.09607 | >0.05             |
| log (SO_{2}) | log(S.I)   | coverage        | None                 | >0.10   | 0.04342 | >0.05             |
| log (SO_{2}) | log(S.I)   | w               | None                 | >0.10   | 0.07813 | 0.00              |
| log (NO_{X}) | log(S.I)   | GDP             | >95%                 | <0.05   | 0.1002  | >0.05             |
| log (NO_{X}) | S.I.        | GDP             | >90%                 | <0.10   | 0.09012 | >0.05             |
| NO_{X}    | S.I.        | GDP             | None                 | >0.10   | 0.01194 | >0.05             |
| log (NO_{X}) | log(S.I)   | population      | >95%                 | <0.05   | 0.09901 | >0.05             |
| log (NO_{X}) | log(S.I)   | ngoogle         | >95%                 | <0.05   | 0.09591 | >0.05             |
| log (NO_{X}) | log(S.I)   | coverage        | >90%                 | <0.10   | 0.08645 | >0.05             |
| log (NO_{X}) | log(S.I)   | w               | None                 | >0.10   | 0.07922 | 0.00              |
Full model details for the four best models are presented below.

1) Dependent variable: log(GHG); Independent variable: log (stringency index); weighting factor: GDP

| Variable name          | Coefficient | t-stat | p-value |
|------------------------|-------------|--------|---------|
| Constant               | -4.900      | -2.02  | 0.058   |
| Log (Stringency Index) | 1.726       | 3.16   | 0.005   |
| Number of observations | 22          |        |         |
| Number of parameters   | 2           |        |         |
| Breusch-Pagan test (p-value) | 0.2435 |        |         |
| R²                     | 0.20225     |        |         |
| Adjusted R²            | 0.16237     |        |         |

2) Dependent variable: log(PM$_{2.5}$); Independent variable: log (stringency index); weighting factor: population

| Variable name          | Coefficient | t-stat | p-value |
|------------------------|-------------|--------|---------|
| Constant               | -11.844     | -5.02  | 0.000   |
| Log (Stringency Index) | 1.308       | 2.35   | 0.029   |
| Number of observations | 22          |        |         |
| Number of parameters   | 2           |        |         |
| Breusch-Pagan test (p-value) | 0.966 |        |         |
| R²                     | 0.13338     |        |         |
| Adjusted R²            | 0.09004     |        |         |

3) Dependent variable: log(SO$_2$); Independent variable: log (stringency index); weighting factor: population

| Variable name          | Coefficient | t-stat | p-value |
|------------------------|-------------|--------|---------|
| Constant               | -9.565      | -4.01  | 0.001   |
| Log (Stringency Index) | 1.178       | 2.11   | 0.048   |
| Number of observations | 22          |        |         |
| Number of parameters   | 2           |        |         |
| Breusch-Pagan test (p-value) | 0.8465 |        |         |
| R²                     | 0.10384     |        |         |
| Adjusted R²            | 0.05904     |        |         |

4) Dependent variable: log(NO$_X$); Independent variable: log (stringency index); weighting factor: GDP

| Variable name          | Coefficient | t-stat | p-value |
|------------------------|-------------|--------|---------|
| Constant               |             |        |         |
| Log (Stringency Index) |             |        |         |
| Number of observations |             |        |         |
| Number of parameters   |             |        |         |
| Breusch-Pagan test (p-value) |         |        |         |
| R²                     |             |        |         |
| Adjusted R²            |             |        |         |
### SI7 – Comparison with other studies

In this section we compare our results with those of other studies as far as possible given the unique nature of each study in terms of background data, methods and methodology.

| Study                  | Period covered       | Result                          | Notes                                                                                                                                 |
|------------------------|----------------------|---------------------------------|---------------------------------------------------------------------------------------------------------------------------------------|
| This research          | Feb 15th – May 29th 2020 | 1000 – 1600 Mt CO₂e             | Emissions reduction due to global personal mobility restriction from the beginning of the pandemic through to end of May 2020. Please note the different measuring unit compared to other studies (CO₂e vs. CO₂) |
| Le Quéré et al. 21     | Jan – Apr 2020       | 1048 (543 – 1638) MtCO₂         | Direct effects in global CO₂ emissions due to the forced confinement during the Covid-19 pandemic                                          |
| Liu et al. 22          | Jan – Mar 2020       | 542Mt CO₂                       | Reduction in global emissions in the first quarter of 2020.                                                                                                                                      |
| This research          | Feb 15th – May 29th 2020 | 1-3% global emissions reduction|                                                                                                                                                                                                    |
| Liu et al. 23          | Jan – Apr 2020       | 7.8% emissions reduction globally | This is a much higher value than what we observe but Liu et al. cover: Industry, Electricity, Residential, Road Transport, and Ship Transport – which is a much broader system boundary than what we include in our emissions reduction |
analysis, thus justifying the discrepancy.

References

1. Lenzen, M.; Geschke, A.; Abd Rahman, M. D.; Xiao, Y.; Fry, J.; Reyes, R.; Dietzenbacher, E.; Inomata, S.; Kanemoto, K.; Los, B.; Moran, D.; Schulte in den Bäumen, H.; Tukker, A.; Walmsley, T.; Wiedmann, T.; Wood, R.; Yamano, N., The Global MRIO Lab - charting the world economy. *Economic Systems Research* 2017, 29, (2), 158-186.

2. UNSD *National Accounts Main Aggregates Database*; https://unstats.un.org/unsd/snaama/; United Nations Statistics Division: New York, USA, 2020.

3. UNSD *National Accounts Official Data*; http://data.un.org/Browse.aspx?d=SNA; United Nations Statistics Division: New York, USA, 2019.

4. UNSD *UN comtrade - United Nations Commodity Trade Statistics Database*; http://comtrade.un.org/; United Nations Statistics Division, UNSD: New York, USA, 2019.

5. World Bank GDP growth (annual %); https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG; World Bank: Washington D.C., USA, 2020.

6. Lenzen, M.; Gallego, B.; Wood, R., Matrix balancing under conflicting information. *Economic Systems Research* 2009, 21, (1), 23-44.

7. Global Warming Potential Values (AR5) Greenhouse Gas Protocol. https://www.ghgprotocol.org/sites/default/files/ghgp/Global-Warming-Potential-Values%20%28Feb%2016%202016%29_1.pdf (8 April),

8. Janssens-Maenhout, G.; Crippa, M.; Guizzardi, D.; Muntean, M.; Schaaf, E.; Dentener, F.; Bergamaschi, P.; Pagliari, V.; Olivier, J. G. J.; Peters, J. A. H. W.; van Aardenne, J. A.; Monni, S.; Doering, U.; Petrescu, A. M. R., EDGAR v4.3.2 Global Atlas of the three major Greenhouse Gas Emissions for the period 1970-2012. *Earth Syst. Sci. Data Discuss.* 2017, 2017, 1-55.

9. LLC, G., "Google COVID-19 Community Mobility Reports." https://www.google.com/covid19/mobility/ Last Accessed: <May 1st>. In 2020.

10. World Bank, GDP (current US$) World Bank national accounts data, and OECD National Accounts data files - Available at https://data.worldbank.org/indicator/NY.GDP.MKTP.CD]. In 2020.

11. Worldometers, World population by country. In 2020.

12. Fountas, G.; Sun, Y.-Y.; Akizu-Gardoki, O.; Pomponi, F., How do people move around? National data on transport modal shares for 131 countries. *World 2020*.

13. Apple, Maps Mobility Trends Reports In 2020.

14. Global Stats Mobile Operating System Market Share Worldwide: Apr 2019 - Apr 2020. https://gs.statcounter.com/os-market-share/mobile/worldwide

15. Ou, S. Q.; He, X.; Ji, W. Q.; Chen, W.; Sui, L.; Gan, Y.; Lu, Z. F.; Lin, Z. H.; Deng, S. L.; Przesmitzki, S.; Bouchard, J., Machine learning model to project the impact of COVID-19 on US motor gasoline demand. *Nature Energy*.

16. Steenge, A. E.; Bočkarjova, M., Thinking about imbalances in post-catastrophe economies: An input–output based proposition. *Economic Systems Research* 2007, 19, (2), 205-223.
17. Lenzen, M.; Sun, Y.-Y.; Faturay, F.; Ting, Y.-P.; Geschke, A.; Malik, A., The carbon footprint of global tourism. *Nature Climate Change* **2018**, *8*, (6), 522.

18. White, H., A HETEROSKEDASTICITY-CONSISTENT COVARIANCE-MATRIX ESTIMATOR AND A DIRECT TEST FOR HETEROSKEDASTICITY. *Econometrica* **1980**, *48*, (4), 817-838.

19. Tischer, V.; Fountas, G.; Polette, M.; Rye, T., Environmental and economic assessment of traffic-related air pollution using aggregate spatial information: A case study of Balnario Camboriu, Brazil. *Journal of Transport & Health* **2019**, *14*.

20. Washington, S.; Karlaftis, M. G.; Mannering, F.; Anastasopoulos, P., *Statistical and econometric methods for transportation data analysis*. CRC Press: 2020.

21. Le Quéré, C.; Jackson, R. B.; Jones, M. W.; Smith, A. J. P.; Abernethy, S.; Andrew, R. M.; De-Gol, A. J.; Willis, D. R.; Shan, Y.; Canadell, J. G.; Friedlingstein, P.; Creutzig, F.; Peters, G. P., Temporary reduction in daily global CO\textsubscript{2} emissions during the COVID-19 forced confinement. *Nature Climate Change* **2020**.

22. Liu, Z.; Deng, Z.; Ciais, P.; Lei, R.; Davis, S.; Feng, S.; Zheng, B.; al., e., COVID-19 causes record decline in global CO2 emissions. In 2020.

23. Liu, Z.; Ciais, P.; Deng, Z.; Davis, S.; Zheng, B.; Wang, Y.; Cui, D.; Zhu, B.; Dou, X.; Ke, P.; Sun, T.; Guo, R.; Boucher, O.; Breon, F.-M.; Lu, C.; Guo, R.; Boucher, E.; Chevallier, F., Carbon Monitor: a near-real-time daily dataset of global CO2 emission from fossil fuel and cement production [preprint available at: https://arxiv.org/abs/2006.07690] In 2020.