# Measuring the impact of COVID-19 confinement measures on human mobility using mobile positioning data. A European regional analysis

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A B S T R A C T

This work presents a mobility indicator derived from fully anonymised and aggregated mobile positioning data. Even though the indicator does not provide information about the behaviour of individuals, it captures valuable insights into the mobility patterns of the population in the EU and it is expected to inform responses against the COVID-19 pandemic. Spatio-temporal harmonisation is carried out so that the indicator can provide mobility estimates comparable across European countries. The indicators are provided at a high spatial granularity (up to NUTS3). As an application, the indicator is used to study the impact of COVID-19 confinement measure on mobility in Europe. It is found that a large proportion of the change in mobility patterns can be explained by these measures. The paper also presents a comparative analysis between mobility and the infection reproduction number $R_t$ over time. These findings will support policymakers in formulating the best data-driven approaches for coming out of confinement, mapping the socio-economic effects of the lockdown measures and building future scenarios in case of new outbreaks.

## 1. Introduction

The coronavirus disease 2019 (COVID-19), caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), rapidly expanded throughout the world during the first quarter of 2020, reaching pandemic status on 11 March. This presented authorities in many countries with unprecedented challenges, with intensive care units in national health systems reaching saturation point. Governments reacted passing a wide range of measures, including information campaigns, fiscal stimulus to support the economy, and confinement measures designed to contain the spread of the virus. The need for timely, accurate and reliable data that would inform such decisions was of paramount importance.

Against this backdrop, on 8 April the European Commission asked European Mobile Network Operators (MNOs) to share anonymised and aggregated mobile positioning data. These data would provide mobility patterns of population groups and would serve the following purposes in the fight against COVID-19:

- "understand the spatial dynamics of the epidemics using historical matrices of mobility national and international flows;

- quantify the impact of physical distancing measures (travel limitations, non-essential activities closures, total lockdown etc.) on mobility, including the phasing out of such measures as relevant;

- feed epidemiological models, contributing to the evaluation of the effects of physical distancing measures on the reduction of the rate of virus spread in terms of reproduction number (expected number of secondary cases generated by one case);

- feed models to estimate the economic costs of the different interventions, as well as the impact of specific control measures on intra-EU cross border flows due to the epidemic."

The aim of the initiative is in line with the European Commission Recommendation to support exit strategies through mobile data and apps.[1] Adding details on how mobile positioning data can contribute to epidemiological models, the Joint European Roadmap towards lifting COVID-19 containment measures of 15 April explains that "[…] mobile network operators can offer a wealth of data on mobility, social interactions […] Such data, if pooled and used in anonymised, aggregated format in compliance with EU data protection and privacy rules, could

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[1] Commission Recommendation (EU) 2020/518 of 8 April 2020 on a common Union toolbox for the use of technology and data to combat and exit from the COVID-19 crisis, in particular concerning mobile applications and the use of anonymised mobility data.

contribute to improve the quality of modelling and forecasting for the pandemic at EU level."

This work focuses on how the mobile positioning data can be used to analyse the impact of the confinement measures on mobility in fourteen EU countries, namely Austria, Belgium, Bulgaria, Croatia, Denmark, Estonia, Finland, France, Germany, Italy, Portugal, Slovenia, Spain and Sweden plus Norway. The paper is organised as follows: Section 2 describes the mobile positioning data at hand. Section 3 introduces the mobility indicator derived from the mobile positioning data. Section 4 assesses the impact of the confinement measures on mobility. Finally, Section 5 provides a comparative analysis between mobility in Italy and the change of the infection reproduction number ($R_t$) in the country. Section 6 summarises the conclusions.

## 2. Mobile positioning data

By means of a letter to European MNOs, the European Commission asked for fully anonymised aggregated mobility data. In compliance with the 'Guidelines on the use of location data and contact tracing tools in the context of the COVID-19 outbreak' by the European Data Protection Board (EDPB, 2020), these data do not provide information about the behaviour of individuals; it can, however, give valuable insights into mobility patterns of population groups. These data received by the JRC are in the form of Origin-Destination Matrix (ODM) (Mamei et al., 2019; Fekih et al., 2020). This section briefly describes what an ODM is; the following section illustrates how the Joint Research Centre builds mobility indicators from the ODMs.

Each cell $[i - j]$ of the ODM shows the overall number of *'movements'* (also referred to as 'trips' or 'visits') that have been recorded from the origin geographical reference area $i$ to the destination geographical reference area $j$ over the reference period. In general, an ODM is structured as a table showing:

- reference period (date and, eventually, time);
- area of origin;
- area of destination;
- count of movements.

Despite the fact that the ODMs provided by different MNOs have similar structure, they are often very heterogeneous. Their differences can be due to the methodology applied to count the movements, to the spatial granularity or to the time coverage. Nevertheless, each ODM is consistent over time and relative changes are possible to be estimated. This allows defining common indicators (such as 'mobility indicators', 'connectivity matrices' (Iacus et al., 2020a) and 'mobility functional areas' (Iacus et al., 2020b)) that can be used, with all their caveats, by JRC in the framework of this joint initiative.

Although the ODM contains only anonymised and aggregate data, in compliance with the EDPB guidelines (EDPB, 2020), upon the reception of each ODM, the JRC carries out a *'Reasonability Test'*. Both the reasonability test and the processing of the ODM to derive mobility indicators take place within the JRC's *Secure Platform for Epidemiological Analysis and Research* (SPEAR).

## 3. Mobility indicators

The 'Mobility Indicator' is a data product that aggregates mobile phone position data (ODMs) at standardised spatial and temporal granularities, thus allowing for an easier comparison of mobility patterns across different European countries. The indicator further aggregates the position data at a daily temporal granularity, and uses the NUTS (Nomenclature of Territorial Units for Statistics[2]) geographic

areas to provide spatial aggregates. Specifically, it aggregates the data at NUTS3, NUTS2, NUTS1 and NUTS0 (or country) level.[3]

The mobility indicator for a given geographic area provides a historical time series of the number of total daily movements in that area. Unlike the connectivity matrices, it does not give information about bilateral movements. However, it disaggregates the movements according to the direction of travel as *internal*, *inwards*, *outwards* and *total*. Using $A$ as a reference area, *internal* movements are those movements that started and ended in $A$; *inward* movements are those that started outside $A$ and ended in $A$; *outward* movements are those that started in $A$ and ended outside $A$; and *total* are all the movements that started or ended in $A$. Some ODMs include residual movements, which in some cases cannot be classified as *internal*, *inwards* or *outwards*. An example of this would be the number of movements from a municipality in $A$ to other municipalities in the country: since it is not known whether the other municipalities are in $A$ or not, it is not possible to label these movements as *internal* or as *outwards*; they are nonetheless included in the *total* category for area $A$.

The mobility indicator is built by aggregating the values of the cells in ODM rows and/or columns. The rows and columns to be aggregated correspond to the geographic areas at the ODM spatial granularity level that belong to the geographic area (at NUTS level) the indicator is built for. Graphically, this is represented in Fig. 1 (left), which represents the usual case in which the indicator refers to a coarser spatial area than the ODM spatial granularity. This could be, for instance, when the ODM is given at municipality level, while the indicator is at NUTS3 level (i.e. province or region): there are several municipalities in the NUTS3 area, and therefore rows and/or columns of the ODM need to be aggregated to compute the indicator. In the figure, the rows of the matrix correspond to the origins (at the ODM spatial granularity), the columns to the destinations, and the content of each cell is the number of movements from a given origin to a given destination. In this example, it is assumed that the NUTS area ($K$) for which the indicator is being calculated includes three spatial areas in the ODM ($k_1$, $k_2$ and $k_3$). The *internal* value of the indicator will be the sum of the ODM cells in orange, since those are the movements that start and end in $K$ (note that movements that start in $k_i$ and end in $k_j$ with $i \mathrel{!=} j$ are also internal to $K$). The *inward* indicator will be the sum of the cells in green: these are the movements that start outside $K$ and end in $K$. Likewise, the *outward* indicator will be the sum of the cells in blue: movements that start in $K$ and end outside $K$. The *total* indicator will be the sum of orange, green and blue cells. Some MNOs do not report values in the main diagonal of the matrix, i.e. it is not known the number of internal movements at the spatial granularity of the ODM. Fig. 1 (right) present how to compute the indicator in those cases, maintaining the same colour scheme for the different constituents of the indicator.

Mathematically, the mobility indicator is described by Eqs. (1)–(4)

$$M_K^{\text{total}}(t) = M_K^{\text{int}}(t) + M_K^{\text{inw}}(t) + M_K^{\text{outw}}(t) \tag{1}$$

$$M_K^{\text{int}}(t) = \sum_{i \in K} \sum_{j \in K} \text{ODM}_{i,j}(t) \tag{2}$$

$$M_K^{\text{inw}}(t) = \sum_{i \notin K} \sum_{j \in K} \text{ODM}_{i,j}(t) \tag{3}$$

$$M_K^{\text{outw}}(t) = \sum_{i \in K} \sum_{j \notin K} \text{ODM}_{i,j}(t) \tag{4}$$

where $M_K^{\text{total}}(t)$, $M_K^{\text{int}}(t)$, $M_K^{\text{inw}}(t)$, $M_K^{\text{outw}}(t)$ are, respectively, the *total*, *internal*, *inwards* and *outwards* mobility indicators for the
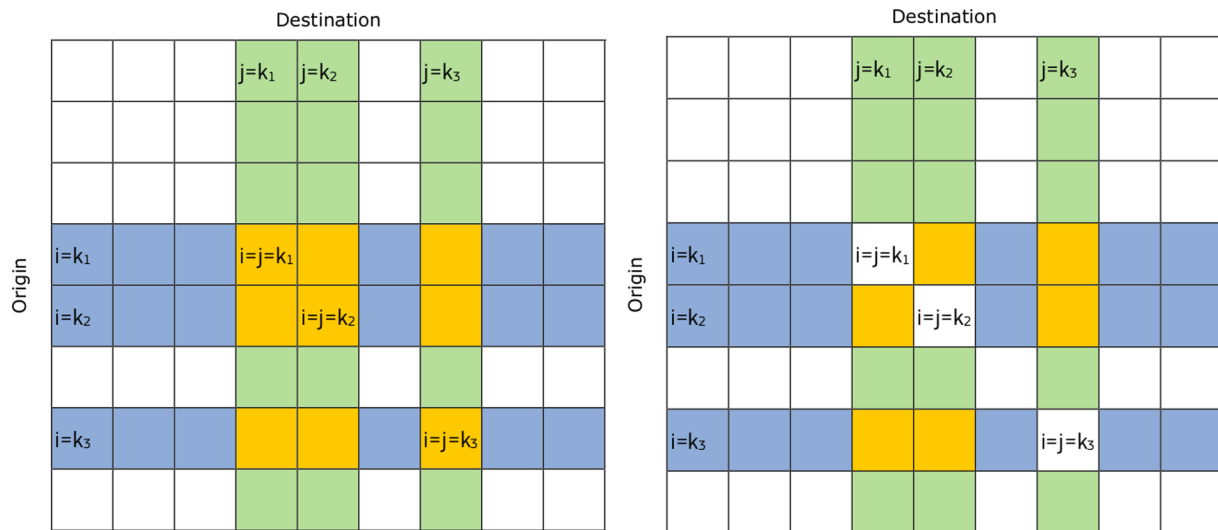
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**Fig. 1.** Left: Mobility indicator construction. The matrix is the original ODM at higher level of spatial granularity than the indicator. The values of the orange cells are aggregated to obtain the *internal* mobility indicator, the blue cells are aggregated into the *outwards* indicator, and the green cells into the *inwards* indicator. Right: Mobility indicator construction when no values for the main diagonal of the ODM are available. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

geographic area $K$ and for time reference $t$; ODM is the original Origin-Destination Matrix at a higher level of spatial granularity than the indicators, $ODM_{i,j}$ is the element of the matrix in row $i$ and column $j$, and $K$ is the set of spatial areas at the original ODM granularity that belong to $K$.

The number of movements reported in the ODMs heavily depend on some parameters used in the construction of the matrices. It is therefore believed that the utility of these data is more in the relative changes along time rather than in their absolute values. For this reason, the indicator is normalised for each country. This means that the indicator for all the NUTS areas of a given country will be normalised by the same factor. As a result, using this normalised indicator it is still possible to know which NUTS areas within a country had higher or lower mobility. Across countries, it is possible to compare the percentage change in mobility. By default, no further aggregation is done temporally, although in some cases such a step could be useful. For instance, a 7-day moving average filters out the significant weekly fluctuations observed in the data (i.e. generally, mobility during working days is much higher than during weekends or holidays).

Fig. 2 compares the mobility indicator for a number of NUTS3 areas in Spain. The chart also disaggregates the movements in *internal*, *inwards*, *outwards* and *total*. In all areas mobility was sharply reduced in the first half of March 2020 as a result of the implementation of lockdown measures. Mobility gradually recovered in April and May, in some areas faster than in others, depending on how quickly the lockdown measures were eased. The vertical red line marks 15 March, the start of the lockdown in Spain. The red dots indicate Sundays; there is a clear weekly mobility pattern, with mobility greatly reduced during weekends. Fig. 3 presents the mobility indicator as a map for the NUTS3 areas of 15 countries. The map on the left shows the reduction in *total* mobility between 28 February and 3 April, when mobility in Europe was at its lowest level; the map on the right compares the indicator between 28 February and 29 May, when the mobility had already recovered much of the ground lost due to the lockdown or, in some areas, it had already surpassed the mobility level last seen in February. It is also clear from the maps that in some countries (e.g. Austria) mobility has changed in a spatially non-uniform way. This emphasises the value of data at sub-national level.

The expected uses of this indicator are in epidemiological and economic modelling, in early warning applications, and to understand the impact of confinement measures on mobility. The following section delves into this last use.

## 4. Impact of the COVID confinement measures on mobility

Almost all countries have imposed a wide range of measures to try and respond to the negative effects of COVID-19. Some of these measures have directly targeted the spread of the virus by limiting social contact. Examples of such measures are the closure of schools or non-essential shops, the banning of large gatherings, or national lockdowns. European contries have already started to lift these confinement measures. The timing and stringency of the measures (or the lifting of the measures) varies from country to country. This section uses the mobility indicator described in previous sections to assess the impact of the confinement measures on mobility across Europe.

Fig. 4 compares the total mobility indicator for the 15 European countries for which mobile phone data dating back to the pre-lockdown weeks is currently available. A 7-day moving average has been applied to the time series to eliminate the weekly mobility patterns. It is evident from the chart that the reduction in mobility was sharp and happened during the first three weeks of March, first in Italy followed a week later by the other countries. After that, the mobility remained low for several weeks, but has gradually recovered as the confinement measures are lifted. While the general mobility pattern is similar for all countries, the magnitude of the reduction of mobility varies significantly between countries: some countries (e.g. Spain, Italy, France, Austria, Portugal) experienced a stricter lockdown that others (e.g. Belgium, Finland, Estonia, Denmark, Norway, Sweden, Romania).

Figs. 5 and 6 show a quantitative analysis of the impact on mobility of the lifting of the measures in Italy and France respectively. The charts also indicates some of the key confinement measures, marking the dates in which they became effective or when they were lifted. In both countries mobility was already marginally increasing before the first de-escalation decision (start of Phase 2 in Italy, and start of Phase 1 in France), but the recovery really accelerated when the decisions became effective. A 7-day moving average has been applied to the mobility indicator to eliminate the weekly mobility patterns.

A number of organisations systematically collect and curate datasets of the confinement measures that authorities around the world implement at national or sub-national regional scopes (see World Health Organization, 2020; Desvars-Larrive et al., 2020; Hale et al., 2020; Lukas Lehner, 2020). These datasets can be used to understand the
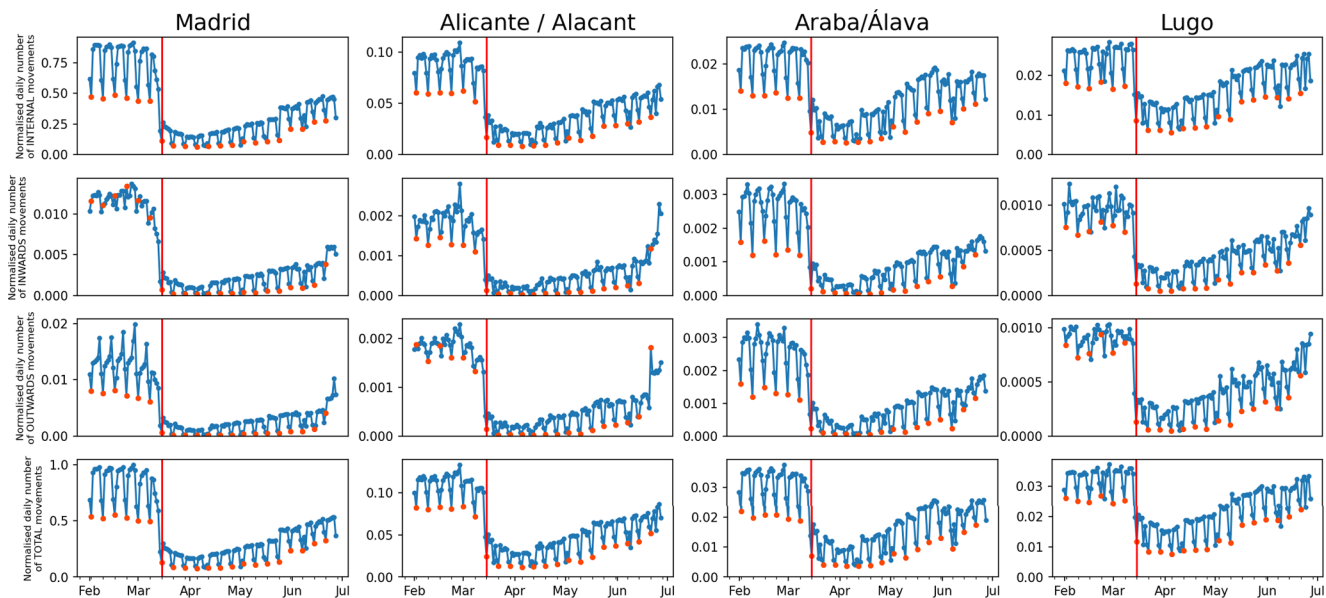
**Fig. 2.** Mobility indicator for four NUTS3 areas in Spain (columns). The rows show (from top to bottom): *internal*, *inwards*, *outwards*, and *total* indicator. Read vertical line marks 15 March, when the national lockdown became effective. The red dots indicate Sundays. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
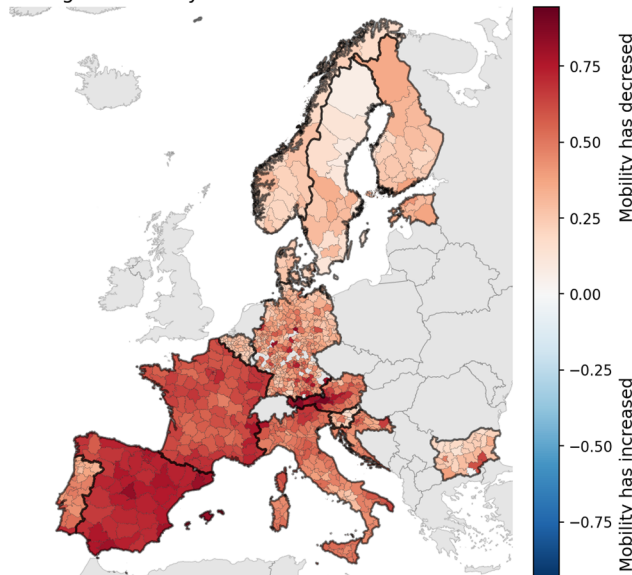
effects of the measures on mobility (see Hussain, 2020). The mobility indicator described in Section 3 has been applied in one such analysis. The study has used data from the Oxford Covid-19 Government Response Tracker (OxCGRT) (Hale et al., 2020), a database that collects information on the type, timing and intensity of the confinement measures taken by countries. The main aim of this analysis is to quantify how much of the observed changes in mobility can be explained by the confinement measures.

Of all the measures available in OxCGRT, the following have been used in this analysis: C1 (closures of schools and universities), C2 (closures of workplaces), C3 (cancelling of public events), C4 (restrictions on gatherings), C5 (closures of public transport), C6 (stay at home requirements), C7 (restrictions on internal movement between cities/ regions), H1 (public information campaigns). Measure C8 (restrictions on international travel) has not been included in the analysis because not all the MNOs provide data on the number of roaming users. In the

database, each of the measures can take a value from 0 to 2, 3 or 4, indicating the intensity with which the measure is applied. So a value of 0 indicates no measure (no public information campaign for H1) and the highest value in the scale indicates complete closure/ban (co-ordinated campaign for H1). Each measure in the OxCGRT database is accompanied by a flag that represents the geographic scope of the measure (targeted or general). Although these flags could be used as an additional gradation of the measures at country level, they are not used in this analysis. It is left for future work the extension of the current analysis to sub-national regions: mobility indicators exist at such level (NUTS1, NUTS2 and NUTS3), but datasets of confinement measures at the same geographic granularity would be required. Such a granular analysis would help to explain the non-uniform regional changes in mobility seen in Fig. 3.

OxCGRT also include a number of policy indices that combine the data of several of the individual measures into composite indicators.
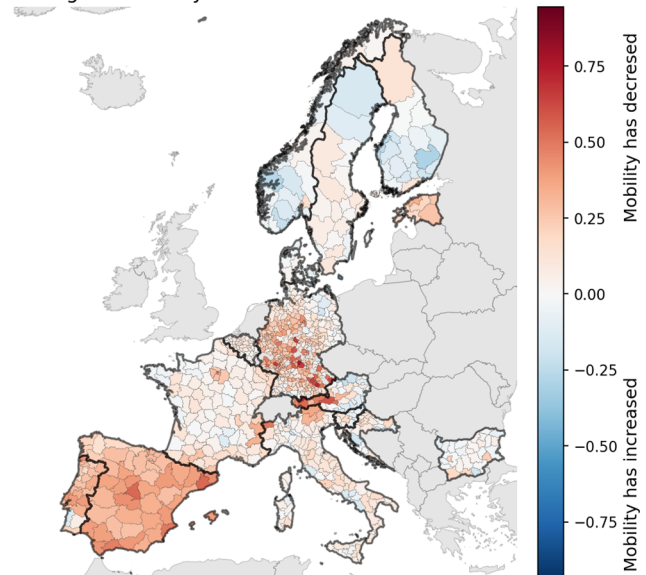


**Fig. 3.** Change in mobility between 28 February and 3 April (left) and between 28 February and 29 May (right).
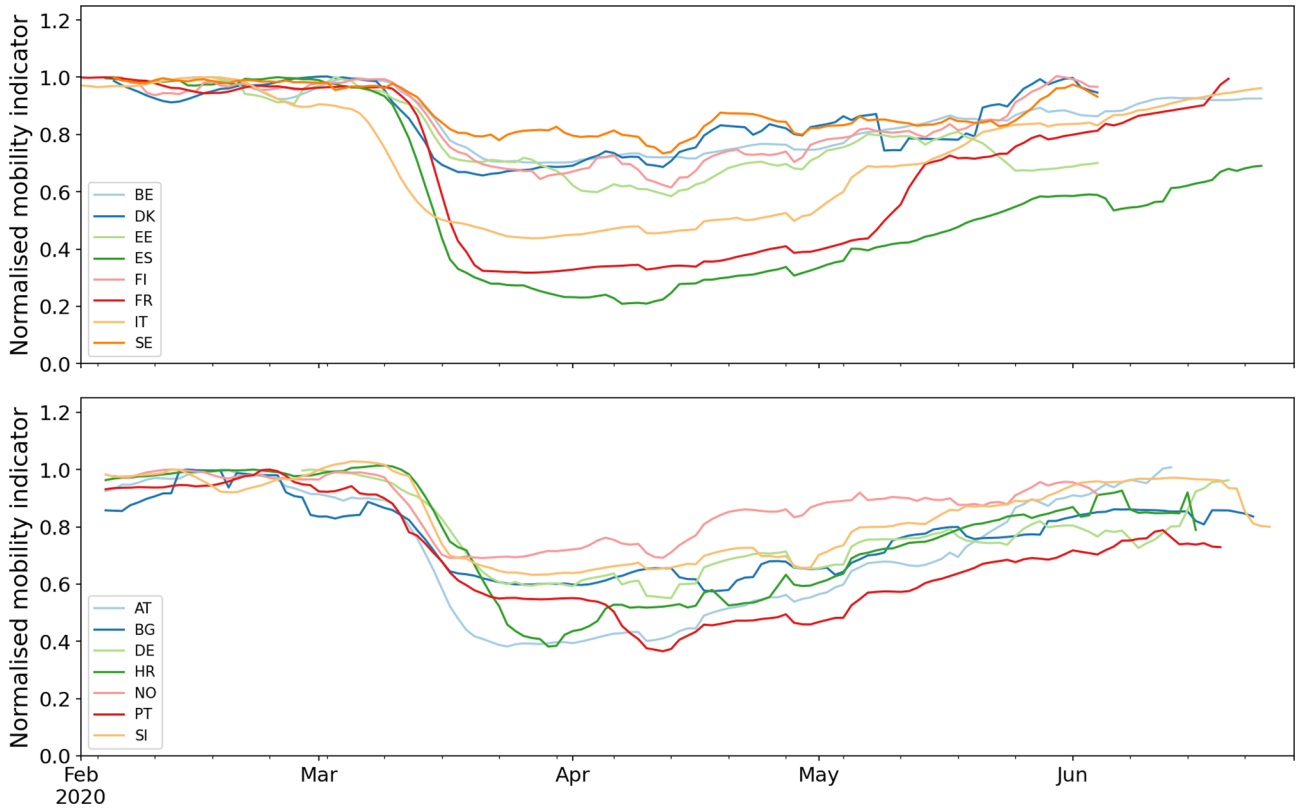
**Fig. 4.** Normalised *total* mobility indicator at country level. The indicator has been smoothed with a 7-day moving average.

The stringency index, which combines all C measures plus H1, has also been used in this analysis.

For a given country and day, OxCGRT gives an integer value between 0 and 4 for each measure and a floating point value from 0 to 100 to the stringency index.

A number of linear regression models have been fitted to the dataset composed of the OxCGRT confinement measures (as independent variables) and the mobility indicator (as dependent variable). A 7-day moving average is applied to the *total* mobility indicator, and this smoothed indicator is used as dependant variable in the models. By averaging the indicator, the weekly mobility patterns (see Fig. 2) are eliminated. This is positive, as far as this analysis is concerned, because the simple models can be then defined with only one explanatory variable, the confinement measure, which is the variable under study. It is therefore easier to evaluate the impact of those measures on mobility, which is the main goal of this analysis. Modelling using the un-smoothed mobility will require an extra dummy variable to encode the type of day (working day or holiday). This dummy variable can itself explain a big part of the changes in mobility observed, and would

therefore confound the findings of the analysis. Alternatively, the models should be fitted to the un-smoothed data points of working days only or weekends only.

The models used are:

- Simple models: one single measure (or the stringency index) is used at a time.
- Full model: all the confinement measures (but not the stringent index) are used.

Mathematically, they are described by Eqs. (5) and (6)

$$mob^c = const + \alpha_i^c \, measure_i^c, \quad \forall \, i \in M, \ \forall \, c \in C \qquad \text{[Simple model } i]$$
(5)

$$mob^c = const + \sum_{i \in M'} \beta_i^c \, measure_i^c, \quad \forall \, c \in C \qquad \text{[Full model]}$$
(6)

where $mob^c$ is the smoothed *total* mobility indicator for country $c$, $measure_i^c$ is the $i^{th}$ OxCGRT confinement measure of country $c$, $M =$
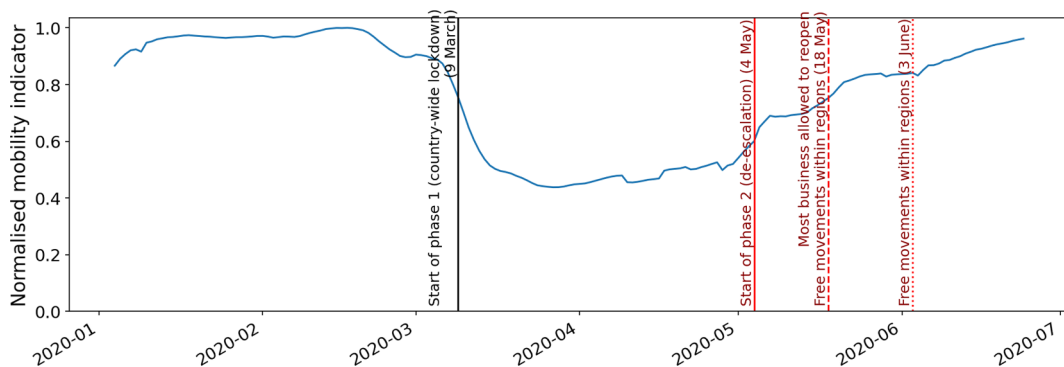


**Fig. 5.** Normalised *total* mobility indicator for Italy (7-day moving average) with key confinement measures marked.
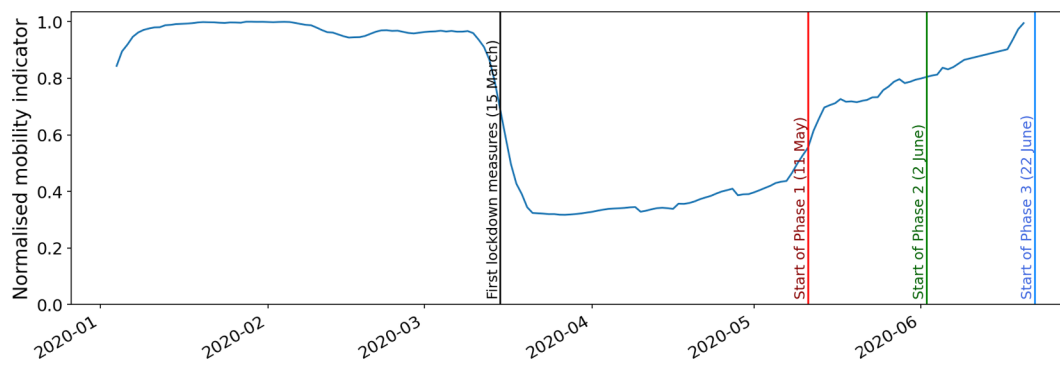
**Fig. 6.** Normalised *total* mobility indicator for France (7-day moving average) with key confinement measures marked.

$\{C1, C2, C3, C4, C5, C6, C7, H1, \text{Stringency index}\}$, $M' = \{C1, C2, C3, C4, C5, C6, C7, H1\}$, $C$ is the set of countries studied, and $\alpha_i^c$ and $\beta_i^c$ are the coefficients of the regression models.

The models are fitted to the data of each country individually or to the data of all the countries. In this last case, dummy variables encoding the country are used.

Fig. 7 presents the coefficient of determination (adjusted $R^2$) for the different models and countries. In the majority of cases, the confinement measures explain more than 50% of the mobility patterns. Some measures do not explain any of the mobility in some countries, because those measures were never implemented in those countries. The full model that combines all the measures manages to explain the highest proportion of the mobility data, followed by the simple model that uses the stringency index. Overall, H1 achieves the lowest $R^2$, perhaps unsurprisingly given that this measure is informative and does not involve enforced closures or bans.

## 5. Comparative analysis between mobility and $R_t$ in Italy

A metric widely used to assess and monitor the growth rate of an outbreak, its transmission potential and the effects of containment interventions is the reproduction number (Bettencourt and Ribeiro, 2008; Heffernan et al., 2005; Svensson, 2007). The reproduction number describes how many persons an infectious individual will on average infect in a certain population. This number is used in many contexts and it has several definitions and symbols to describe it. We can distinguish between the *basic* and the *effective* reproduction Number. The *basic* reproduction number $R_0$ describes how many persons an infectious person infects totally on average during his or her time being infectious in a population where nobody is assumed to have any protection against the disease. Thus, it describes in most situations what happens if a new disease enters a population. The *effective* reproduction number $R_t$

describes how many persons an infectious person infects totally on average during his or her time being infectious in a population where some individuals can have protection against the disease. This value thus describes how much an infection can spread at different timepoints depending on the immunity of the population. The effective reproduction number in this study is mentioned as $R_t$ where $t$ denotes time. Several models can be used to calculate $R_t$ from the epidemiological data (daily incidence). There is not a standard method to calculate the reproduction number, and we generally use 4 of the most common methods. The quality of the estimation depends strongly on the quality of the reported data in terms of quantity, timeliness and representativeness. There can also be irregularities in the data, such as reporting delays and changes in testing practices. These can result in data breaks. The estimation of the reproduction number in Italy has been performed by applying several models to the epidemiological data collected. Some models have a quicker reaction to the changes in the number of cases, other have more inertia to the changes (e.g. $R_t$ 7d, which is based on the ratio between the cases of the last week and the cases of the previous week), but are more stable and ignore sudden peaks. The reproduction number can be formulated as:

$$R_t = \tau\, c\, d \tag{7}$$

where $\tau$ is the transmission probability per contact, $c$ is the contact rate (number of contacts between individuals per unit time) and $d$ is the infectious period. It could be said that the transmission probability is a function of the aggressivity of the epidemic but also of the implementation of non-pharmaceutical measures, such as the use of masks and physical distancing. The contact rate can be correlated with the mobility as a proxy for the number of daily contacts of the people. The infectiousness period depends only on the type of epidemics.

Fig. 8 compares the evolution of the mobility in Italy with four estimates of $R_t$. All the estimation models show a very good correlation with the mobility indicator, with a slow reduction in $R_t$ from the time of
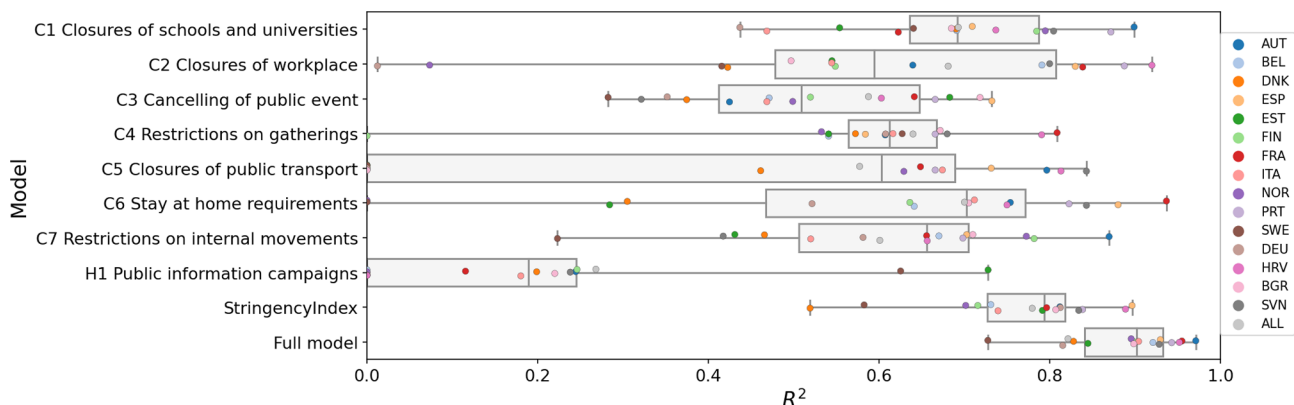


**Fig. 7.** Adjusted $R^2$ for the models evaluated (horizontally). One boxplot is computed for each model based on the distribution of $R^2$ values for the different countries (coloured dots). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
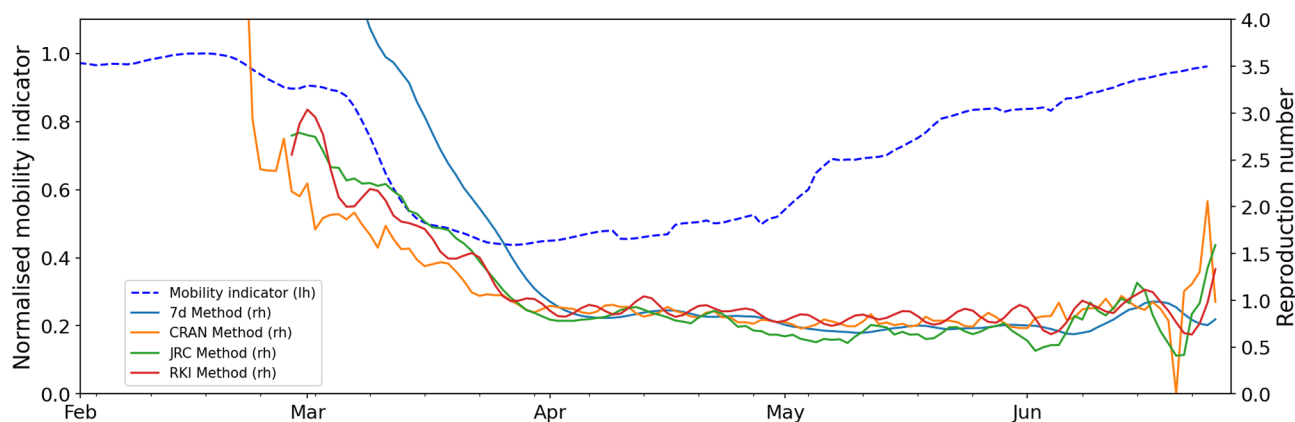
**Fig. 8.** Comparison of the mobility indicator (dashed line, left hand axis) in Italy and four different estimates of $R_t$ (solid lines, right hand axis).

the lockdown and for about 2 weeks, until 26 March. The interpretation of the trends observed is as follows. During the initial part of the epidemics, people did not use face masks or maintain physical distance. Changes in the contact rate, and thus changes in mobility, were a good indicator of $R_t$. However, the increase in the contact rate after the lifting of the lockdown, as demonstrated by the increase in mobility, is not automatically reflected in an increase of $R_t$. This can be observed in the period after 4 May, when the mobility recovered a large part of the lost ground during the lockdown but $R_t$ remained almost constant. The increase in $R_t$ observed in the last days of June was due to the recalculation of the number of positive cases in one of the Italian regions and therefore it is not a reliable indicator of a pick up in the reproduction number. The lack of correlation between increased recovered mobility after 4 May and Rt demonstrates the importance of physical distancing measures.

## 6. Conclusions

The paper describes a mobility indicator based on fully anonymised and aggregated mobile positioning data. The indicator is harmonised spatially and temporally for European countries, and can be produced at a high spatial granularity (up to NUTS3 level, corresponding to population sizes ranging from 150 000 to 800 000). The indicator is then used to assess the impact on mobility of the confinement measures designed to stop the spread of COVID-19, first qualitative for two countries (Italy and France) and then quantitative using a database with the timing and intensity of the measures in several countries. This later analysis shows that the confinement measures explain up to 90% of the mobility patterns. This analysis can be expanded as data from more countries are received. Additionally, the study could be applied at subnational level if harmonised and easy to use data on the confinement measures at that spatial level become available. The indicator is also used to compare mobility with the infection reproduction number $R_t$.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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