Mining Google and Apple mobility data:
Twenty-one shades of European social distancing measures for COVID-19

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We employ the mobility data released by Google and Apple to investigate the effects of social distancing on the spreading dynamics of COVID-19 in Europe. We identify and quantify different degrees of social distancing and characterise their imprint on the first wave of the pandemic. The analysis allows us to classify countries according to their level of mobility. Furthermore we identify a negative change in the infection rate occurring two to five weeks after the onset of mobility reduction for the European countries studied here.

I. INTRODUCTION

COVID-19 has disrupted our way of living with long lasting impact on our social behaviour and the world economy. At the same time, differently from earlier pandemics, a very large amount of data has been collected thanks, also, to our smartphone dominated society. Smartphones run mobility applications, such as Google and/or Apple Maps, that help humans navigate. The mobility information stemming from these apps has been harvested by Google and Apple, which have subsequently made it publicly available on the following websites: www.google.com/covid19/mobility and www.apple.com/covid19/mobility.

In this paper we mine these data to achieve a better understanding of the effects of social distancing measures enacted by various European countries. An early study of mobility effects on the pandemic evolution in China can be found in Ref. [1]. The Google mobility data, in Google wordings, show movement trends by region, across different categories of places. As categories we will use “Residential” and “Workplace”, which best describe the change in people’s behaviour after the implementation of social distancing measures with respect to a baseline day. The latter is defined, according to Google, as the median value from the 5-week period from the 3rd of January to the 6th of February, 2020, predating the wide spread of the virus in Europe. The data show how visitors to (or time spent in) categorised places changed with respect to the baseline day. For Apple, the available mobility data represent a relative volume of direction requests per country/region, sub-region or city, compared to a baseline volume defined on the 13th of January, 2020. We will be using, from Apple, information about “Driving” and “Walking”, assuming they represent the time spent by people away from home.

Another set of data relevant for this work is related to the virus spreading dynamics, which we take from the website ourworldindata.org. We normalise the data of each country as cases per million inhabitants.

The data relative to the total number of infected cases are effectively parameterised using the High Energy Physics inspired formalism introduced in [2], dubbed epidemic Renormalisation Group (eRG). The approach has been generalised to take into account the spreading dynamics across different regions of the world in [3] and the evolution of the second wave pandemic across Europe [4]. The advantage of the eRG formalism resides in the limited number of coefficients needed to classify the spreading dynamics for each country. More complicated models have been used in the literature to study the effect of non-pharmaceutical interventions, including mobility, for Europe [5] and in the USA [6-10], with the latter mostly focusing on local communities.

Without further ado, following [2,3], we introduce $\alpha(t)$ below

$$\alpha(t) = \ln (I(t)) ,$$

where $I(t)$ is the total number of infected cases per million inhabitants in a given country and ln indicates its natural logarithm. The function $\alpha(t)$ turns out to be well described by the following logistic function:

$$\alpha(t) = \frac{ae^{\gamma t}}{b+e^{\gamma t}} .$$

Here, $a$ represents the logarithm of the final number of infected cases per million inhabitants, $b$ denotes the temporal shift from the start of the pandemic and $\gamma$ measures
the flatness of the curve of the number of new infected cases. Here, and in the following, we will measure the time $t$ in weeks, so that $\gamma$ is measured in inverse weeks. It was argued in [2, 3] that, aside from the trivial temporal shift provided by $b$ and for the first wave of the pandemics, two numbers are sufficient to characterise the evolution of the number of infected cases per each county, i.e. $a$ and $\gamma$. This fact helps studying the correlation between mobility data and the virus spreading dynamics for each country. By going beyond the previous parameterisation we will discover a finer temporal structure directly related to the effects of the imposed lockdown and social distancing measures in the different countries.

In this work we focus on Europe, and study in detail the countries listed in Table I. We considered only countries with more than 3 millions inhabitants and for which the data were available. Note that we will only consider the period during which the first wave of the COVID-19 was raging in Europe. Using Google and Apple data, we provide a rationale to identify the timing of the social distancing measure actualisation in each country. In our approach, this is defined in terms of the reduction in the individuals’ mobility rather than on political decisions. We will also show that Google and Apple data are positively correlated, thus consolidating our results. For example, we will discover that Italy, France, Portugal and Spain are the countries showing the highest rate of mobility reduction (high immobility, HI), while Sweden shows the least reduction (low immobility, LI). All the other countries place themselves in between these extreme limits.

We now move to analyse possible correlations between mobility data and the parameters of the logistic function $a(t)$. We will show, to our surprise, that $\gamma$ is not correlated to the degree of mobility reduction. This would naively imply that the severity of the mobility reductions has little impact on the variations of this parameter. Of course, mobility data only capture one aspect of the social distancing, thus they do not offer a complete picture of the situation in various countries.

To push further the analysis, we explored whether social distancing measures (as defined via the Apple/Google mobility data) lead to distinct temporal patterns in the European countries under study. In the eRG approach, $\gamma$ is the natural candidate parameter to use for this task. One could imagine that, after the measures are enacted, there would be two distinct temporal regions describing the time dependence of the number of infected cases. These two regions would be described by two different gammas. To establish whether it is, at all, possible to extract these two values we first provide a MonteCarlo analysis according to which we randomly generate data deviating from an ideal two-gamma model curve. We then move to the actual data and discover that it is possible to identify two distinct temporal regions with their own gammas for several countries. Most of the countries show a transition between the two temporal regions 2-5 weeks after the beginning of the implementation of the social distancing measures. The results suggest that this is the time needed for the measures to become effective. Furthermore, we observe a systematic decrease of the value of $\gamma$ by $25 \div 45\%$, resulting in a flatter epidemic curve.

The paper is organised as follows: In Section II we provide the rationale for classifying countries based on the Google/Apple mobility data; In Section III we compare the mobility data to the features related to the virus spreading dynamics in Europe; In Section IV we show that two temporal regions exist (parameterised by two different $\gamma$’s) due to enforcing social distancing measures. We finally conclude in Section V.

II. HIGH VERSUS LOW IMMOBILITY

European countries adopted different degrees of social distancing measures during the first wave of the COVID-19 pandemic. Moreover the severity of the measures changed during the spreading of the epidemic within each country. Rather than classifying the countries based on their political choices, we use the mobility data provided by Google and Apple as indicators of the effective hardness of the measures.

Therefore, we mine Google’s Residential and Workplace mobility data since they show movement trends across different places compared to a reference period before the implementation of any measure, as discussed in the introduction. The Residential and Workplace data are best suited to quantify when and to what extent people reduced their mobility and increased social isolation. The normalisation of the data and the time span is explained in the introduction, and further details can be found on the website www.google.com/covid19/mobility. Similarly, for Apple, we choose the Driving and Walking data, expressing them in terms of a percentage reduction. Note that the Apple data refer to variations in the number of searches done on the Maps app, more details to be found on the website www.apple.com/covid19/mobility.

To define a measure for the immobility of a given population during the social measure period, we define, for each of the four categories, the average percentage variation. The beginning of the period for each country is identified with the time when Google Workplace percentage drops by 20% (at this time, typically, all mobility indicators have shown a significant variation). The ending of the measure period is harder to identify, as the social distancing measures have always been lifted progressively: this appears in the mobility data, as the curves gradually return to zero, i.e. to the reference period levels. Thus, we decided to fix the same averaging period for all the countries we considered. To test the robustness of our conclusions, we determine the outcome for two choices: 6 and 8 weeks after the beginning of the measures. The results are shown in the top panels of Fig. I for Google (left) and Apple (right) data respec-
FIG. 1: Tadpole plots showing correlations between the four mobility reduction categories: Residential and Workplace from Google, Driving and Walking from Apple. The head of the tadpoles correspond to the average over 6 weeks after the measure beginning, while the tail indicates the 8 week average. The countries in red are identified as HI, while the one in magenta as LI.

In all plots, the head of the tadpoles refer to the 6 week average, which always reveals a stronger mobility reduction.

The two plots reveal a clear correlation between the mobility reduction in the data. We also identify two sets of countries that always feature the strongest and weakest mobility reduction for both Google and Apple data: France, Spain, Italy and Portugal (highlighted in red) feature high immobility (HI), while Sweden (highlighted in magenta) features low immobility (LI). The other countries (in blue) line up in between the two extreme cases.

To further illustrate this feature, in the remaining four tadpole plots of Fig. 1 we display all correlations between Google and Apple data for all countries. We clearly observe that the distinction between HI and LI countries persists. We will, therefore, use this characterisation in the following analyses.
III. COMPARING THE VIRUS SPREADING DYNAMICS WITH MOBILITY INDICATORS

To characterise the virus spreading dynamics in each country under study, we fit the number of infected cases, taken from ourworldindata.org to the logistic function in Eq. (2). For an optimal extraction of $\gamma_i$ and $a_i$, we include in the fit the data from the day when the number of cases passes 10 individuals, and stop when the plateau is reached. The latter choice is due to the fact that, in most cases, the would-be plateau features a linear growth in the number of cases, which is not included in the model. More details on the fitting can be found in Ref. [2]. The fit parameters we obtain are listed in Table I. We remind the reader that, while the time-dependence of the pandemic, encoded by the $\gamma_i$’s, provides a robust information, the total number of infected cases, encoded in the $a_i$’s, depends on the different counting strategies adopted by each country. Thus, we consider correlations involving the epidemic strength $\gamma$ to be more meaningful.

We now ask whether there is any correlation between mobility data and the values of the parameters $\gamma$ and $a$. In fact, it is reasonable to expect that the stronger the social distancing measures (i.e., more reduced individual mobility) the slower the epidemic diffusion (i.e., smaller $\gamma$). However, we do not observe any significant correlation, as exemplified in Fig. 2, where we compare the four mobility categories with the infection rate $\gamma$ for the set of countries in this study. The symbols, resembling racecars, should be interpreted as follows: the pilot seat (dot) indicates the 6 week average mobility indicator with the body of the car (the line segment) pointing towards the 8 week average result, while the car traction system (horizontal bars) indicates the error on $\gamma$ from the fits. As it is evident from the wide spread distribution of the racecars, no correlation emerges between $\gamma$ and the immobility indicators.

This surprising finding can be interpreted in various ways. On the one hand, the result may imply that the main factor behind a reduction of $\gamma$ could lie in the behaviour of individuals in social occasions (mask wearing, proximity, greeting habits, to mention a few); on the other hand, it is quite possible that the value of $\gamma$ does not represent the effect of the social distancing measures, as it derives from a global fit over a wide timescale. In other words, the fit values include both the measure and the pre-measure periods. We will further investigate and test this possibility in the next section.

IV. TESTING THE TWO-GAMMA HYPOTHESIS

As mentioned in the previous section, we did not find any significant correlation between the infection rate $\gamma$ and the mobility data. We just mentioned that this finding could be due to the fact that we are fitting the data to a single $\gamma$, which averages over pre and post-measure data for each country. Here we test the possibility that social distancing measures lead to a time-dependent $\gamma$. The latter is modeled by two distinct time-intervals with each its own constant $\gamma$. We therefore subdivide the period of the virus diffusion in 3 parts, as illustrated in the left panel of Fig. 3. Region A extends up to the time when the measures start, $t = 0$, as defined in Section II from the mobility data; at this point starts Region B, which extends for a duration $\Delta t$; finally Region C starts at $t = \Delta t$. As the beginning of Region B is determined by the Google/Apple mobility data, we can probe the existence of a change in $\gamma$ by fitting the data in Region B+C with the following function:

$$\alpha_2(t) = \begin{cases} 
\frac{a \exp(\gamma B t)}{b + \exp(\gamma B t)} & \text{for } t < \Delta t \\
\frac{a \exp(\gamma C t)}{b \exp(\gamma C t) + \exp(\gamma C t)} & \text{for } t > \Delta t
\end{cases}$$

that depends on 5 parameters: $a$, $b$, $\gamma_B$, $\gamma_C$ and $\Delta t$. We then extract the values of the 5 parameters by fitting to the data.

We first test the effectiveness of our method by generating a mock set of data based on the function in Eq. (3), where we fix $\gamma_B = 0.7$, $\gamma_C = 0.35$ and $\Delta t = 20$ days. An example of the generated data, overlaid to the generating function, is shown in the right panel of Fig. 3. The points are randomly generated within a one standard deviation region, i.e. $[N_i \pm \sqrt{N_i}, N_i + \sqrt{N_i}]$, where $N_i$ is the number of new cases per day as predicted by the generating function. We generated 100 independent sets of mock data and fitted them to Eq. (3). We found that we can determine the value of $\Delta t$ with a week precision.

Having acquired confidence in the method, we now apply it to the real data for the countries listed in Table I. For all countries, we find a good fit for the two-gamma model, with the results shown in Fig. 4. In the two left plots, we show the values of $\Delta t$ (i.e. the duration of Region B) obtained from the fits including their relative error, together with an histogram showing their distribution within the sampled countries. We observe that most of the countries feature a $\Delta t$ between 2 to 5 weeks. This could be considered as the characteristic time it takes for the social distancing measures to produce an effect on the virus diffusion. The countries with larger values are typically countries with a smaller population, for which the statistic is worse. In some cases, this is indicated by the larger error bar on $\Delta t$.

In the right plots, we also show the difference of the infection rates in percentage, defined as

$$\Delta \gamma = \frac{\gamma_C - \gamma_B}{\gamma_C}.$$ 

Most countries show $\Delta \gamma$ between $-45\%$ and $-25\%$, demonstrating that a reduction in the infection rate always occurs. Interestingly, there is no clear distinction between the HI and LI countries from this result. There are two outliers with larger values, corresponding to Poland and Slovakia. In both cases, the fit picks up
a feature in the data that seems to come from a lack of statistics.

V. DISCUSSION

We analysed the mobility data released by Google and Apple to quantify the effects of social distancing on the COVID-19 spreading dynamics in Europe. We were able to classify different shades of social distancing measures
for the first wave of the pandemic. After identifying the countries according to their level of immobility, we demonstrated the existence of a negative change in the infection rate occurring two to five weeks after the onset of mobility reduction for the countries studied here. Thus we have provided an actual measure of the impact of social distancing measures for each country via $\Delta \gamma$, showing that the effect amounts to a reduction by 25% to 45% for most countries in the study. This is, to the best of our knowledge, a first direct measure of the impact of social distancing in Europe. Interestingly even Sweden shows a negative $\Delta \gamma$ of the same order as the one for high immobility countries, suggesting that a certain degree of social restrain occurred regardless of the political decisions. This result is compatible with early analysis of social distancing measures taken in China [1], where mobility data inter-cities from [baidu] have been used within a compartmental model.

Our results prove that social distancing can be timed via mobility data from smartphones, as provided by Google and Apple, and that the effect on the pandemic diffusion has a characteristic time, independent on the severity of the mobility reduction. This timing can also be used to quantify the impact of social distancing by determining the variation in infection rate, $\Delta \gamma$, per country. Finding similar $\Delta \gamma$, however, does not imply that the countries have a similar number of infected cases per million inhabitants. It simply means that there has been a change in social behaviour. The result of this study, based on the economic eRG approach, lays the basis for a simple tool that can allow local and centralised authorities to evaluate the timing and impact of the imposition of social distancing measures, in particular related to movement restrictions.

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Author contribution

This work has been designed and performed conjointly and equally by the authors. G.C., C.C. and F.S. have equally contributed to the writing of the article.
| Country | ISO code | a          | γ          | b          |
|--------|----------|------------|------------|------------|
| Austria | AUT      | 7.4414 ± 0.0032 | 0.989 ± 0.015 | 4.36 ± 0.23 |
| Belgium | BEL      | 8.5267 ± 0.0029 | 0.5403 ± 0.0055 | 2.099 ± 0.059 |
| Bulgaria | BGR      | 6.103 ± 0.013 | 0.3357 ± 0.0074 | 1.506 ± 0.052 |
| Croatia | HRV      | 6.2952 ± 0.0034 | 0.719 ± 0.0126 | 1.646 ± 0.062 |
| Denmark | DNK      | 7.6321 ± 0.0057 | 0.4333 ± 0.0068 | 1.218 ± 0.038 |
| France  | FRA      | 7.7033 ± 0.0033 | 0.6115 ± 0.0078 | 3.48 ± 0.15 |
| Germany | DEU      | 7.6289 ± 0.0042 | 0.4333 ± 0.0068 | 1.218 ± 0.038 |
| Hungary | HUN      | 6.0172 ± 0.013 | 0.5043 ± 0.0070 | 2.137 ± 0.067 |
| Ireland | IRL      | 8.5438 ± 0.0023 | 0.6077 ± 0.0061 | 2.325 ± 0.070 |
| Italy   | ITA      | 8.2595 ± 0.0036 | 0.4770 ± 0.0061 | 1.730 ± 0.057 |
| Netherlands | NLD | 7.8860 ± 0.0031 | 0.5563 ± 0.0050 | 2.211 ± 0.051 |
| Norway  | NOR      | 7.3108 ± 0.0043 | 0.645 ± 0.011 | 1.771 ± 0.075 |
| Poland  | POL      | 6.628 ± 0.026 | 0.317 ± 0.012 | 1.516 ± 0.078 |
| Portugal | PRT      | 7.9612 ± 0.0070 | 0.580 ± 0.012 | 1.894 ± 0.094 |
| Romania | ROU      | 6.9766 ± 0.0087 | 0.4900 ± 0.0075 | 1.707 ± 0.062 |
| Serbia  | SRB      | 7.4223 ± 0.0032 | 0.6261 ± 0.0070 | 3.27 ± 0.12 |
| Slovakia | SVK      | 5.6456 ± 0.0065 | 0.641 ± 0.018 | 2.45 ± 0.18 |
| Spain   | ESP      | 8.4932 ± 0.0038 | 0.6809 ± 0.0099 | 2.93 ± 0.14 |
| Sweden  | SWE      | 8.433 ± 0.014 | 0.2910 ± 0.00545 | 1.280 ± 0.036 |
| Switzerland | CHE | 8.1652 ± 0.0016 | 0.7571 ± 0.0060 | 2.713 ± 0.068 |
| United Kingdom | GBR | 8.4002 ± 0.0056 | 0.3989 ± 0.0051 | 2.512 ± 0.084 |

**TABLE I**: Countries considered in this study and their fit parameters for the one-gamma model.

**Competing interests**

The authors declare no competing interests.

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| Country     | ISO code | a       | $\gamma_B$       | $\gamma_C$       | b       | $\Delta t$       |
|-------------|----------|---------|------------------|------------------|---------|------------------|
| Austria     | AUT      | 7.4647 ± 0.0028 | 1.062 ± 0.012 | 0.729 ± 0.020 | 0.788 ± 0.015 | 2.378 ± 0.053 |
| Belgium     | BEL      | 8.5624 ± 0.0082 | 0.5308 ± 0.0063 | 0.381 ± 0.026 | 0.975 ± 0.020 | 6.09 ± 0.14    |
| Bulgaria    | BGR      | 6.350 ± 0.074  | 0.281 ± 0.014  | 0.155 ± 0.023  | 1.275 ± 0.034 | 8.69 ± 0.18    |
| Croatia     | HRV      | 6.3132 ± 0.0058 | 0.732 ± 0.013  | 0.547 ± 0.041  | 1.141 ± 0.038 | 4.14 ± 0.23    |
| Denmark     | DNK      | 7.6822 ± 0.0093 | 0.4618 ± 0.0087 | 0.344 ± 0.013  | 0.893 ± 0.025 | 4.52 ± 0.17    |
| France      | FRA      | 7.7382 ± 0.0048 | 0.6385 ± 0.0075 | 0.447 ± 0.016  | 0.793 ± 0.015 | 3.897 ± 0.095  |
| Germany     | DEU      | 7.6690 ± 0.0049 | 0.7055 ± 0.0089 | 0.500 ± 0.014  | 0.722 ± 0.014 | 3.012 ± 0.078  |
| Hungary     | HUN      | 6.077 ± 0.014  | 0.5017 ± 0.0078 | 0.366 ± 0.024  | 1.800 ± 0.049 | 5.86 ± 0.15    |
| Ireland     | IRL      | 8.5533 ± 0.0047 | 0.6081 ± 0.0071 | 0.510 ± 0.038  | 1.527 ± 0.044 | 6.55 ± 0.35    |
| Italy       | ITA      | 8.2823 ± 0.0011 | 0.6037 ± 0.0051 | 0.4080 ± 0.0021 | 0.7609 ± 0.0079 | 2.771 ± 0.031 |
| Netherlands | NLD      | 7.903 ± 0.011  | 0.5424 ± 0.0085 | 0.462 ± 0.053  | 0.769 ± 0.013 | 6.14 ± 0.37    |
| Norway      | NOR      | 7.3715 ± 0.0058 | 0.6521 ± 0.0068 | 0.383 ± 0.015  | 0.6267 ± 0.0084 | 3.570 ± 0.054 |
| Poland      | POL      | 6.983 ± 0.034  | 0.457 ± 0.014  | 0.1969 ± 0.0063 | 2.30 ± 0.11  | 4.172 ± 0.056  |
| Portugal    | PRT      | 8.0027 ± 0.0068 | 0.754 ± 0.026  | 0.482 ± 0.012  | 1.498 ± 0.089 | 2.888 ± 0.087  |
| Romania     | ROU      | 7.0387 ± 0.0055 | 0.555 ± 0.012  | 0.3438 ± 0.0042 | 1.923 ± 0.067 | 3.603 ± 0.060  |
| Serbia      | SRB      | 7.471 ± 0.011  | 0.6049 ± 0.0085 | 0.388 ± 0.034  | 2.026 ± 0.056 | 6.440 ± 0.099  |
| Slovakia    | SVK      | 6.222 ± 0.074  | 0.392 ± 0.018  | 0.0338 ± 0.0044 | 1.507 ± 0.039 | 6.372 ± 0.050  |
| Spain       | ESP      | 8.5248 ± 0.0029 | 0.7581 ± 0.0082 | 0.5237 ± 0.0097 | 0.816 ± 0.015 | 3.050 ± 0.056  |
| Switzerland | CHE      | 8.1750 ± 0.0015 | 0.7809 ± 0.0057 | 0.641 ± 0.013  | 0.5600 ± 0.0062 | 3.021 ± 0.099 |
| Sweden      | SWE      | 8.584 ± 0.018  | 0.3418 ± 0.0076 | 0.2309 ± 0.0051 | 0.891 ± 0.020 | 3.89 ± 0.11    |
| United Kingdom | GBR | 8.4395 ± 0.0038 | 0.5012 ± 0.0092 | 0.3510 ± 0.0034 | 1.250 ± 0.034 | 3.671 ± 0.073  |

TABLE II: Countries considered in this study and their fit parameters for the two-gamma model.