Mining Google and Apple mobility data:

Temporal Anatomy for COVID-19 Social Distancing

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Supplementary material

Materials and Methods

Figs. S1-S4

Tables S1-S4

Materials and Methods

Immobility indicator. European countries and US states 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 or state. 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.

To find a measure for the *immobility* of a given population during the social distancing period, we define an average percentage variation for each of the four categories: Residential and Workplace for Google and Driving and Walking for Apple (only Driving is available for US states). For both mobility datasets, the percentage variations are defined with respect to a reference date or period predating the exponential growth of the infection cases. The data are typically very jugged, as illustrated in Fig. 1, mainly due to strong variations over the weekend. Furthermore, the mobility data feature a sharp decrease followed by a slow return to the pre-COVID-19 average. Taking into account this behaviour, it is necessary to define an average over several weeks, which would allow us to associate a single number to each category and region.

Firstly, one needs to properly define the beginning of the social distancing period for each region: we choose to identify it with the time when Google Workplace percentage first 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 (*3*): this appears in the mobility data, as the curves gradually return to zero, i.e. to the reference period levels, or even above. Thus, we decided to fix the same averaging period for all the regions we considered. To test the robustness of our conclusions, we determine the outcome for two choices: 6 and 8 weeks after the effective beginning of

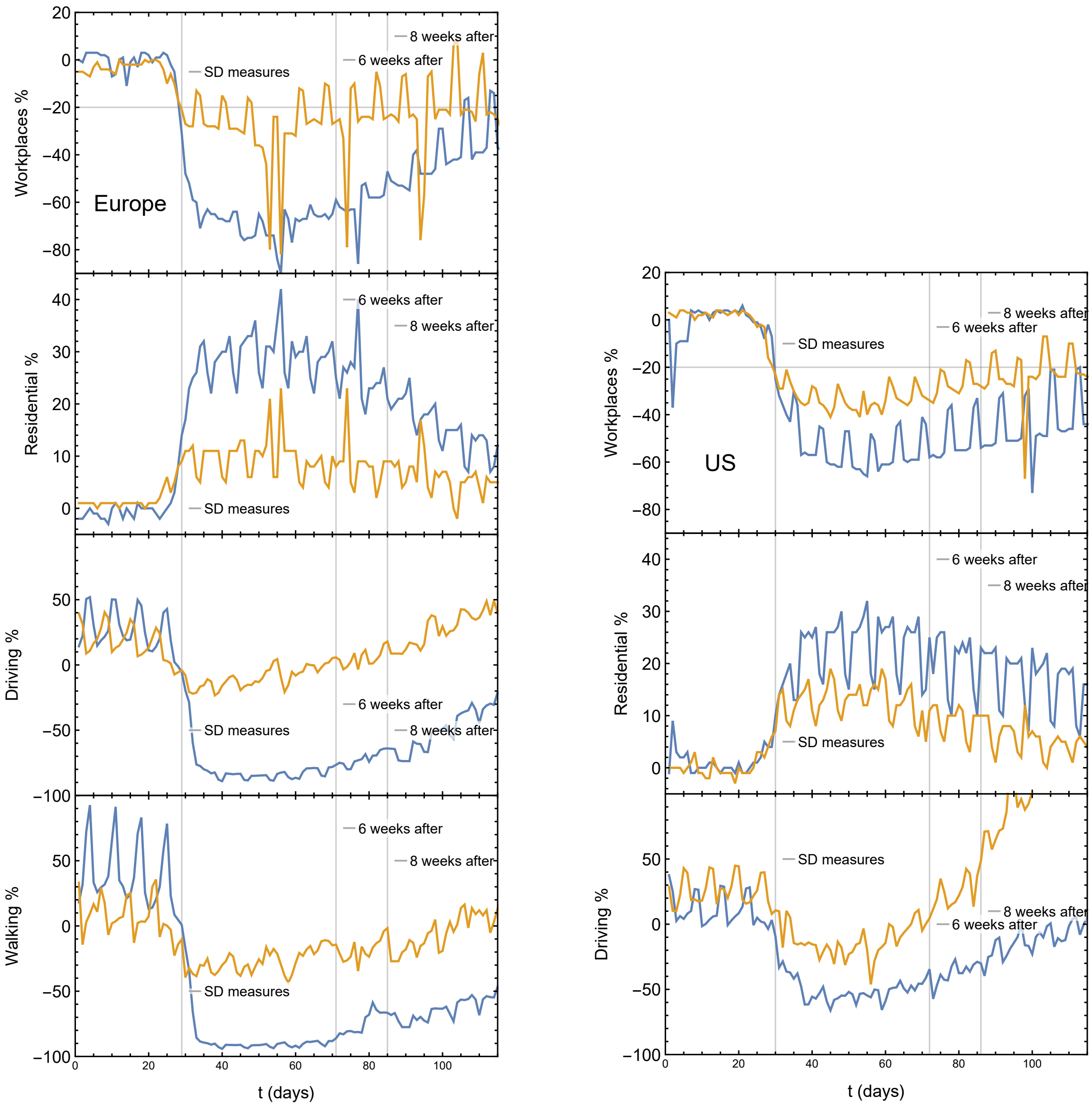

Figure 1: **Raw Google and Mobility data.** In these plots we show a sample of raw Google and Apple mobility data used in this work, for Europe (left) and the US (right). The time scale is shifted so that the beginning of the social distancing, defined by a 20% drop in Google's Workplace and indicated by the first vertical grey line, coincides for all countries and states. The other two vertical lines mark the end of the 6 and 8 week averaging periods respectively. We show the respective HM region in orange and the LM one in blue: for Europe, Sweden (orange) and Spain (blue); for the US, Wyoming (orange) and New York (blue).

the measures. The tadpole-like plot at the bottom of Fig.1 in the main text demonstrate that the duration of the averaging period, while changing the value of the mobility reduction, does preserve the overall trend. In the following, therefore, we will use the 6-week average as our benchmark.

To be able to classify the countries based on their immobility, we further define an immobility indicator as

$$\not{\mathbb{M}}(\text{region}) = \sum_{j=\text{cat.}} \frac{|p_j(\text{region})|}{\max[|p_j|]}\,, \tag{1}$$

where $|p_j(\text{region})|$ is the absolute value of the percentage variation in each category (labelled by j). For each category, we divide by the maximal value observed in the pool. Note that for European countries we have 4 categories, so that $\not{\mathbb{M}} < 4$, while for the US states we have 3 categories, so that $\not{\mathbb{M}} < 3$. We use this indicator to rank the European countries and the American states from the ones with *high mobility* (HM) – small $\not{\mathbb{M}}$ – to the one with *low mobility* (LM) – large $\not{\mathbb{M}}$. The values of the immobility indicator we obtain for the European countries under study and US states are shown in Fig. 2. The colour code ranges from the highest mobility region in bright red to the lowest mobility one in cyan, with gradient proportional to the value of the immobility indicator.

Comparing the virus spreading parameters with mobility data. The epidemic evolution of the first wave of the CODIV-19 pandemic can be effectively characterised by two parameters: the infection rate γ and the logarithm of the final number of total infected cases a (*5*), measured per million inhabitants. We remark, however, that it is risky to compare the number of infected for different regions due to the different procedures used when identifying the positive cases, and the different testing rates and strategies. Thus, we assign more physical meaning to the infection rates γ, which give an accurate temporal characterisation of the epidemic diffusion in each region.

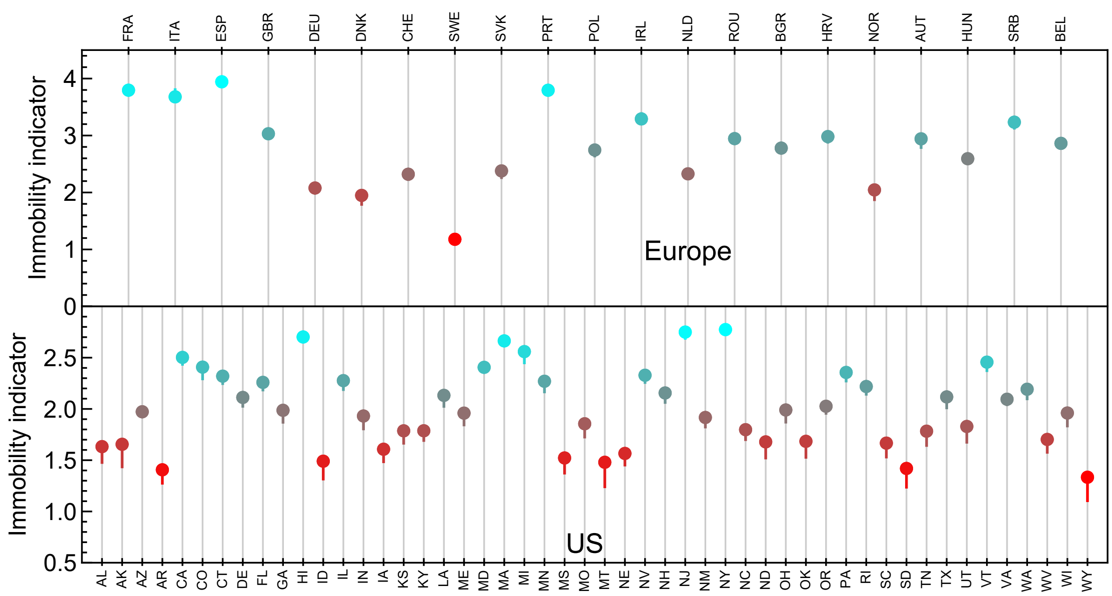

Figure 2: **Immobility indicator for the European countries and the US states.** Values of the immobility indicator $\mathbb{M}$ for Europe (top) and the US (bottom). The colour code corresponds to the ranking of each European country and each US state, matching the one used in Fig.1 of the main text.

It is, therefore, natural to hypothesise that regions with higher mobility may have a faster diffusion rate of the infection, i.e. larger values of γ. To test this hypothesis, in Fig. 3, we show the Workplace, Residential and Driving reductions versus the infection rates for the European countries in this study and the US states. To each country or state is associated a racecar-like symbol: the pilot seat (dot) corresponds to the 6-week average, while the tail to the 8-week average. Furthermore, the side bars indicate the error from the fits of the epidemic data. The colour codes match the immobility indicator defined above. The data used to generate the plots in Fig. 3 are reported in Tables 1 and 3, where we only report the mobility averages over 6 weeks.

Surprisingly, the data do not reveal any particular correlation between the values of γ and

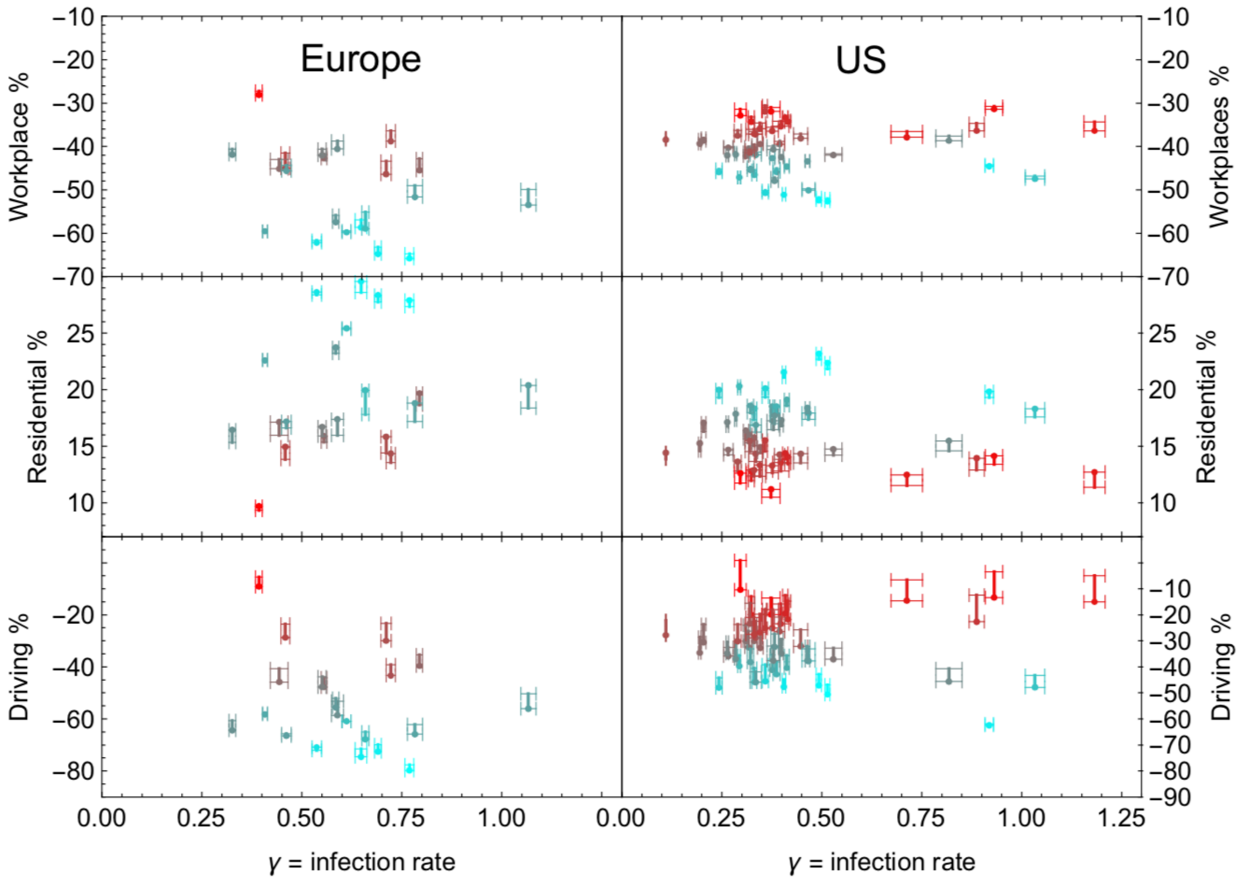

Figure 3: **Infection rate compared to the mobility data**. Racecar plots showing the fitted infection rates γ versus the Google/Apple mobility categories. The vertical segment indicates the difference between 6 week (dot) and 8 week averages; the horizontal bars indicate the fit error on γ.

the mobility data. As explained in the main text, this result can be interpreted in various ways. One possibility, which we will test in the following section, is that the γ from the fit of the first wave is not the most appropriate measure, as it averages over the infection diffusion before and after the mobility reduction occurs.

Testing the two-gamma hypothesis. We subdivide the period of the virus diffusion in 3 parts, as illustrated in the left panel of Fig. 4. Region A extends up to the time when the social distanc-

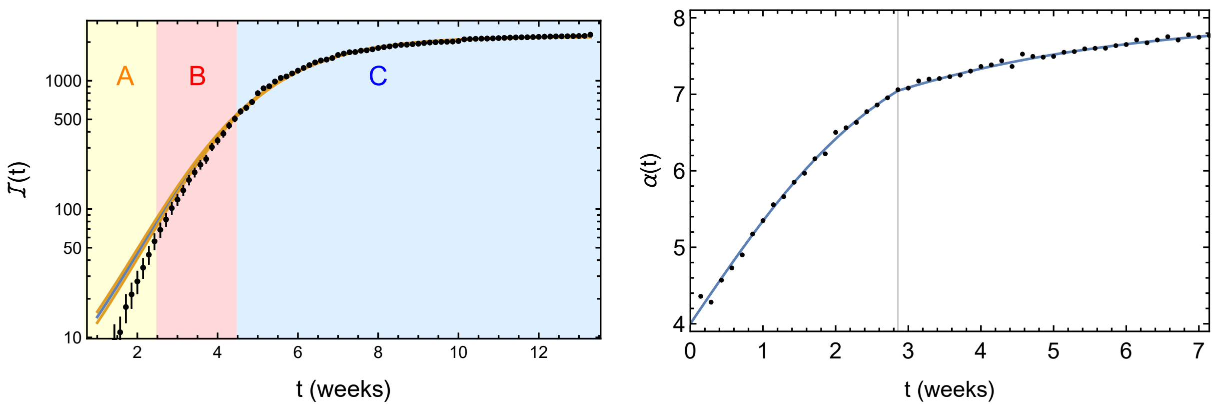

Figure 4: **Temporal anatomy of the first wave epidemic data**. Left panel: schema of the 3 temporal regions defined in the text. A refers to the pre-measure time, B occurs between the start of the social distancing and the change in γ, C covers the later times, after the measure effects occur. The duration of B is defined as Δt. Right panel: generating function (solid) and sample of the simulated points for the two-gamma model.

ing starts, $t = 0$, as defined from the mobility data; at this point Region B begins extending for a duration Δt; 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 γ by fitting the data in Region B+C with the following function:

$$\alpha_{2\gamma}(t) = \begin{cases} a\frac{\exp(\gamma_B t)}{b+\exp(\gamma_B t)} & \text{for } t < \Delta t \\ \\ a\frac{\exp(\gamma_C t)}{b\exp((\gamma_C-\gamma_B)\Delta t)+\exp(\gamma_C t)} & \text{for } t > \Delta t \end{cases} \tag{2}$$

that depends on 5 parameters: a, b, γ_B, γ_C and Δt. 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. (2), 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. 4: the points are randomly generated within a one standard deviation region, i.e. $[N_i - \sqrt{N_i}, N_i + \sqrt{N_i}]$, where N_i is the number of cases per day as predicted by the generating function. We generated 100 independent sets of mock data and fitted them to Eq. (2). We found that we can determine

Fit parameters: first wave and 6-week average mobility variations in Europe								
Country	ISO	a	γ	b	Work.	Res.	Driv.	Walk.
France	FRA	7.641(5)	0.690(8)	$1.20(3) \times 10^3$	−65	28	−73	−82
Italy	ITA	8.185(11)	0.536(12)	106(3)	−62	29	−71	−76
Spain	ESP	8.432(6)	0.769(11)	$1.88(5) \times 10^3$	−66	28	−80	−87
United Kingdom	GBR	8.293(8)	0.407(6)	65(2)	−59	23	−58	−55
Germany	DEU	7.580(7)	0.722(12)	$1.58(4) \times 10^3$	−39	14	−43	−40
Denmark	DNK	7.591(13)	0.458(11)	42(2)	−45	15	−29	−35
Switzerland	CHE	8.142(3)	0.794(8)	$2.45(4) \times 10^3$	−45	20	−40	−40
Sweden	SWE	8.07(3)	0.392(9)	52.6(7)	−28	10	−9.1	−27
Slovakia	SVK	6.00(6)	0.44(2)	139(7)	−45	17	−46	−47
Portugal	PRT	7.90(1)	0.648(14)	$9.5(4) \times 10^2$	−59	30	−75	−84
Poland	POL	6.01(2)	0.588(15)	$9.6(4) \times 10^2$	−41	17	−59	−70
Ireland	IRL	8.541(7)	0.612(11)	$9.8(5) \times 10^2$	−60	25	−61	−66
Netherlands	NLD	7.884(6)	0.555(7)	277(5)	−43	16	−48	−47
Romania	ROU	6.877(17)	0.461(12)	176(8)	−46	17	−66	−73
Bulgaria	BGR	6.13(2)	0.326(8)	40(2)	−42	16	−64	−68
Croatia	HRV	6.25(1)	0.78(2)	$4.7(2) \times 10^3$	−52	19	−66	−64
Norway	NOR	7.261(6)	0.710(13)	$0.84(2) \times 10^3$	−46	16	−30	−37
Austria	AUT	7.410(6)	1.07(2)	$5.9(2) \times 10^4$	−53	20	−56	−64
Hungary	HUN	5.961(11)	0.55(1)	$6.5(3) \times 10^2$	−42	17	−48	−69
Serbia	SRB	7.399(7)	0.658(9)	$2.68(9) \times 10^3$	−59	20	−68	−71
Belgium	BEL	8.498(8)	0.585(8)	338(7)	−57	24	−56	−43

Table 1: **First wave fits and average mobility reductions in Europe**. Values of the fit for a, b and γ for the first wave in the 21 European countries considered in this study, together with the 95% CL error. Six week average mobility reduction for Google and Apple categories.

the value of Δt within a range of two weeks. Furthermore, we define the percentage variation of the infection rate as

$$\Delta\gamma = \frac{\gamma_C - \gamma_B}{\gamma_C} \,. \tag{3}$$

Having acquired confidence in the method, we now apply it to the real data. The results of the fits are reported in Tables 2 and 4.

Fit parameters: two-gamma function parameters in Europe						
Country	ISO	a	γ_B	γ_C	b	Δt
France	FRA	$7.663(9)$	$0.715(13)$	$0.64(2)$	$1.65(4) \times 10^3$	$2.6(2)$
Italy	ITA	$8.304(9)$	$0.591(6)$	$0.386(8)$	$215(3)$	$2.88(4)$
Spain	ESP	$8.483(9)$	$0.79(1)$	$0.62(2)$	$2.68(5) \times 10^3$	$2.74(8)$
United Kingdom	GBR	$8.339(4)$	$0.549(9)$	$0.363(3)$	$429(9)$	$2.78(5)$
Germany	DEU	$7.637(15)$	$0.726(13)$	$0.57(3)$	$1.75(4) \times 10^3$	$2.84(11)$
Denmark	DNK	$8.06(11)$	$0.38(2)$	$0.18(2)$	$24(1)$	$4.60(6)$
Switzerland	CHE	$8.158(7)$	$0.80(1)$	$0.71(3)$	$2.53(4) \times 10^3$	$2.8(2)$
Sweden	SWE	$8.51(11)$	$0.353(12)$	$0.26(2)$	$39(1)$	$3.57(8)$
Slovakia	SVK	$6.04(7)$	$0.56(25)$	$0.43(3)$	$5(2) \times 10^2$	$1.4(1.2)$
Portugal	PRT	$7.95(1)$	$0.80(2)$	$0.548(14)$	$6.7(4) \times 10^3$	$2.61(8)$
Poland	POL	$6.25(3)$	$0.622(12)$	$0.416(16)$	$1.70(5) \times 10^3$	$3.07(5)$
Ireland	IRL	$8.70(4)$	$0.52(2)$	$0.26(4)$	$337(15)$	$6.26(9)$
Netherlands	NLD	$7.900(5)$	$0.67(3)$	$0.528(7)$	$1.18(5) \times 10^3$	$1.91(14)$
Romania	ROU	$7.04(2)$	$0.557(13)$	$0.34(1)$	$7.0(3) \times 10^2$	$3.87(7)$
Bulgaria	BGR	$6.15(2)$	$0.86(31)$	$0.32(8)$	$1.9(7) \times 10^4$	$1.3(2)$
Croatia	HRV	$6.296(8)$	$1.04(4)$	$0.672(15)$	$1.07(7) \times 10^5$	$1.89(7)$
Norway	NOR	$7.42(4)$	$0.62(2)$	$0.32(4)$	$349(6)$	$3.54(5)$
Austria	AUT	$7.462(12)$	$1.060(17)$	$0.75(5)$	$6.1(2) \times 10^4$	$2.35(7)$
Hungary	HUN	$5.972(11)$	$0.95(22)$	$0.54(1)$	$8(3) \times 10^4$	$1.5(2)$
Serbia	SRB	$7.44(3)$	$0.641(14)$	$0.55(5)$	$2.18(8) \times 10^3$	$5.14(18)$
Belgium	BEL	$8.481(17)$	$0.585(11)$	$0.62(4)$	$335.15(8)$	$3.7(6)$

Table 2: **First wave fits for the two-gamma model for Europe**. Outcome of the two-gamma fits for the 5 parameters a, γ_B, γ_C, b and Δt. The errors refer to a 95% CL.

Fit parameters: first wave and 6-week average mobility variations in the US							
State		a	γ	b	Work.	Res.	Driv.
Alabama	AL	$7.92(5)$	$0.40(2)$	$74(4)$	-35	14	-23
Alaska	AK	$6.196(7)$	$0.89(2)$	$2.1(2)\times10^4$	-36	14	-23
Arizona	AZ	$8.28(7)$	$0.266(12)$	$17.5(6)$	-40	15	-36
Arkansas	AR	$7.72(9)$	$0.37(2)$	$63(3)$	-32	11	-20
California	CA	$8.44(4)$	$0.243(8)$	$12.3(5)$	-46	20	-48
Colorado	CO	$8.01(1)$	$0.331(6)$	$31(1)$	-47	18	-46
Connecticut	CT	$9.124(4)$	$0.413(6)$	$73(3)$	-45	19	-40
Delaware	DE	$7.577(7)$	$0.399(5)$	$121(4)$	-43	17	-35
Florida	FL	$9.76(2)$	$0.335(14)$	$20(2)$	-42	17	-46
Georgia	GA	$11.21(2)$	$0.316(9)$	$16.3(7)$	-41	16	-32
Hawaii	HI	$6.578(2)$	$0.919(11)$	$2.81(8)\times10^4$	-45	20	-62
Idaho	ID	$7.751(16)$	$0.71(4)$	$2.2(3)\times10^3$	-38	12	-15
Illinois	IL	$8.93(3)$	$0.322(8)$	$34(2)$	-45	19	-38
Indiana	IN	$8.312(12)$	$0.331(6)$	$35(2)$	-41	16	-30
Iowa	IA	$9.721(13)$	$0.415(7)$	$169(8)$	-34	14	-22
Kansas	KS	$9.12(7)$	$0.335(17)$	$53(4)$	-37	14	-29
Kentucky	KY	$6.71(3)$	$0.395(13)$	$120(6)$	-39	14	-26
Louisiana	LA	$8.424(11)$	$0.82(3)$	$8(1)\times10^3$	-39	15	-46
Maine	ME	$7.237(11)$	$0.195(3)$	$6.7(2)$	-39	15	-35
Maryland	MD	$10.170(7)$	$0.293(3)$	$21.2(5)$	-47	20	-40
Massachusetts	MA	$10.110(3)$	$0.405(4)$	$64(2)$	-51	22	-48
Michigan	MI	$10.820(9)$	$0.359(8)$	$14.6(6)$	-51	20	-46
Minnesota	MN	$8.727(11)$	$0.376(6)$	$137(6)$	-43	19	-41
Mississippi	MS	$7.88(2)$	$0.324(7)$	$36(1)$	-34	13	-20
Missouri	MO	$7.11(2)$	$0.447(18)$	$132(8)$	-38	14	-32
Montana	MT	$4.390(5)$	$1.18(3)$	$1.1(7)\times10^5$	-36	13	-15
Nebraska	NE	$8.75(8)$	$0.409(7)$	$233(12)$	-33	14	-20
Nevada	NV	$7.08(2)$	$0.467(16)$	$149(9)$	-50	18	-38
New Hampshire	NH	$8.704(4)$	$0.285(2)$	$18.8(3)$	-42	18	-37
New Jersey	NJ	$11.340(5)$	$0.493(7)$	$127(4)$	-52	23	-47
New Mexico	NM	$8.06(2)$	$0.346(7)$	$59(2)$	-39	15	-33
New York	NY	$12.530(3)$	$0.514(6)$	$110(4)$	-53	22	-51
North Carolina	NC	$10.73(3)$	$0.1100(16)$	$3.55(3)$	-38	14	-28
North Dakota	ND	$5.22(1)$	$0.358(6)$	$151(6)$	-32	16	-25
Ohio	OH	$9.993(14)$	$0.310(7)$	$21.4(7)$	-42	16	-30
Oklahoma	OK	$6.45(3)$	$0.345(14)$	$45(3)$	-36	13	-27
Oregon	OR	$6.68(2)$	$0.53(2)$	$2.8(3)\times10^2$	-42	15	-37
Pennsylvania	PA	$9.8(1)$	$0.387(9)$	$45(3)$	-46	19	-43
Rhode Island	RI	$7.155(5)$	$0.464(6)$	$2.7(1)\times10^2$	-43	18	-38
South Carolina	SC	$9.21(3)$	$0.376(15)$	$39(3)$	-36	13	-25
South Dakota	SD	$6.041(12)$	$0.93(2)$	$2.1(2)\times10^5$	-31	14	-13
Tennessee	TN	$6.99(3)$	$0.290(9)$	$25(1)$	-38	14	-30
Texas	TX	$9.79(4)$	$0.379(16)$	$48(3)$	-41	17	-38
Utah	UT	$9.69(4)$	$0.320(12)$	$20.4(7)$	-41	16	-23
Vermont	VT	$4.662(5)$	$1.03(2)$	$1.6(2)\times10^5$	-47	18	-48
Virginia	VA	$10.64(1)$	$0.264(3)$	$16.0(4)$	-42	17	-35
Washington	WA	$7.896(13)$	$0.382(9)$	$18(2)$	-48	18	-32
West Virginia	WV	$8.04(4)$	$0.33(2)$	$26(2)$	-37	13	-28
Wisconsin	WI	$8.93(4)$	$0.204(6)$	$7.7(2)$	-39	17	-31
Wyoming	WY	$7.60(4)$	$0.296(15)$	$20(1)$	-33	13	-10

Table 3: **First wave fits and average mobility reductions in the US**. Same as Table 1.

Fit parameters: two-gamma function parameters in the US						
State		a	γ_B	γ_C	b	Δt
Alaska	AK	6.219(6)	1.28(8)	0.80(2)	$2.9(3) \times 10^6$	1.52(8)
Arizona	AZ	8.87(7)	0.48(3)	0.186(6)	$3.7(3) \times 10^3$	2.87(6)
Arkansas	AR	7.9(2)	0.9(4)	0.33(3)	$2.2(8) \times 10^4$	1.2(3)
California	CA	8.80(5)	0.41(3)	0.179(6)	$1.5(2) \times 10^2$	3.6(1)
Colorado	CO	8.056(9)	0.63(6)	0.301(5)	$1.7(2) \times 10^3$	2.7(2)
Connecticut	CT	9.156(4)	0.480(8)	0.333(7)	215(8)	5.3(2)
Delaware	DE	7.596(7)	0.59(5)	0.379(6)	$2.1(3) \times 10^3$	3.6(2)
Florida	FL	10.16(5)	0.51(3)	0.172(9)	$2.6(2) \times 10^2$	3.55(7)
Georgia	GA	11.40(2)	0.45(2)	0.228(6)	126(6)	3.86(8)
Hawaii	HI	6.586(7)	0.91(2)	0.7(2)	$2.89(9) \times 10^4$	4.9(4)
Idaho	ID	7.95(2)	1.23(5)	0.31(2)	$2.6(3) \times 10^6$	2.66(3)
Illinois	IL	9.07(3)	0.53(4)	0.283(6)	$6.3(6) \times 10^2$	2.8(1)
Indiana	IN	8.378(8)	0.62(3)	0.293(4)	$1.9(3) \times 10^3$	3.01(6)
Iowa	IA	10.3(1)	0.33(2)	0.18(2)	62(2)	7.38(5)
Kansas	KS	9.14(9)	0.6(6)	0.33(2)	$1(1) \times 10^3$	1.9(1.3)
Kentucky	KY	6.66(9)	0.40(3)	0.5(1)	130(6)	6.9(6)
Louisiana	LA	8.65(3)	0.91(3)	0.31(3)	$3.7(2) \times 10^4$	3.35(4)
Maine	ME	7.279(9)	0.53(6)	0.180(3)	$5.7(7) \times 10^3$	2.6(2)
Maryland	MD	10.197(6)	0.48(3)	0.277(3)	$3.3(3) \times 10^2$	3.7(2)
Massachusetts	MA	10.138(4)	0.441(6)	0.339(6)	120(3)	5.8(2)
Michigan	MI	10.902(6)	0.47(2)	0.274(4)	66(2)	2.55(7)
Minnesota	MN	8.695(8)	0.23(2)	0.400(5)	16(1)	4.9(2)
Mississippi	MS	8.00(2)	0.50(4)	0.284(6)	$4.0(3) \times 10^2$	2.9(2)
Missouri	MO	7.32(3)	0.66(3)	0.30(2)	$2.9(2) \times 10^3$	3.07(7)
Montana	MT	4.389(6)	1.18(3)	0.767(0)	$1.33(9) \times 10^6$	7.7(0)
Nebraska	NE	8.748(9)	0.36(9)	0.411(8)	$1.2(4) \times 10^2$	4(2)
Nevada	NV	7.24(2)	0.73(3)	0.333(9)	$5.2(4) \times 10^3$	2.89(5)
New Hampshire	NH	8.705(4)	0.284(3)	0.095(0)	19.5(3)	19(0)
New Jersey	NJ	11.361(3)	0.71(2)	0.447(4)	$2.3(1) \times 10^3$	2.83(6)
New Mexico	NM	8.18(3)	0.49(3)	0.306(6)	$4.8(4) \times 10^2$	3.6(1)
New York	NY	12.529(4)	0.513(7)	0.0855(0)	115(3)	18(0)
North Carolina	NC	10.88(3)	0.28(3)	0.103(1)	43(4)	3.9(2)
North Dakota	ND	5.26(2)	0.45(3)	0.331(8)	$7.0(8) \times 10^3$	4.9(3)
Ohio	OH	10.18(3)	0.351(7)	0.222(8)	46(2)	5.29(9)
Oklahoma	OK	6.71(3)	0.68(3)	0.230(7)	$4.7(4) \times 10^3$	3.17(5)
Oregon	OR	7.02(5)	0.70(3)	0.30(2)	$2.0(2) \times 10^3$	2.80(6)
Pennsylvania	PA	9.942(5)	0.60(2)	0.296(4)	$9.5(4) \times 10^2$	3.88(4)
Rhode Island	RI	7.195(4)	0.533(7)	0.384(6)	$8.4(3) \times 10^2$	5.47(8)
South Carolina	SC	9.57(5)	0.50(2)	0.23(2)	$2.7(2) \times 10^2$	3.17(7)
South Dakota	SD	6.04(2)	0.93(3)	0.333(0)	$2.4(2) \times 10^5$	8.7(0)
Tennessee	TN	7.3(2)	0.25(2)	0.18(4)	18.0(7)	6.6(3)
Texas	TX	10.56(9)	0.43(2)	0.19(1)	147(5)	3.79(4)
Utah	UT	10.01(4)	0.48(6)	0.232(6)	208(8)	2.89(5)
Vermont	VT	4.75(2)	0.98(3)	0.36(6)	$1.06(5) \times 10^6$	3.72(6)
Virginia	VA	10.67(1)	0.43(6)	0.256(4)	$1.7(3) \times 10^2$	3.4(3)
Washington	WA	8.20(2)	0.349(5)	0.204(5)	15.3(2)	2.36(4)
West Virginia	WV	9.4(5)	0.35(4)	0.09(2)	67(5)	4.15(8)
Wisconsin	WI	9.13(3)	0.45(4)	0.176(4)	$2.2(2) \times 10^2$	2.6(1)
Wyoming	WY	7.9(3)	0.25(4)	0.17(7)	13.0(7)	7.3(5)

Table 4: **First wave fits for the two-gamma model for the US**. Same as Table 2.