Population mobility reductions during COVID-19 epidemic in France under lockdown

Giulia Pullano[1,2,†], Eugenio Valdano[1,†], Nicola Scarpa[1], Stefania Rubrichi[2,*], Vittoria Colizza[1,*,°]

1 INSERM, Sorbonne Université, Pierre Louis Institute of Epidemiology and Public Health, Paris, France.
2 Orange Labs, Sociology and Economics of Network and Services (SENSE), Chatillon, France.

† Co-first authors

* Contributed equally

° *vittoria.colizza@inserm.fr*

ABSTRACT

On March 17, 2020, French authorities implemented a nationwide lockdown to respond to COVID-19 epidemic emergency and curb the surge of patients requiring critical care, similarly to other countries. Evaluating the impact of lockdown on population mobility is important to help characterize the changes in social dynamics that affected viral diffusion. Using travel flows reconstructed from mobile phone trajectories, we measured how lockdown altered mobility patterns at both local and country scales. Lockdown caused a 65% reduction in countrywide number of displacements, and was particularly effective in reducing work-related short-range mobility, especially during rush hours, and recreational long-range trips. Anomalous increases in long-range movements, localized in both time and space, emerged even before lockdown announcement. Mobility drops were unevenly distributed across regions. They were strongly associated with active population, workers employed in sectors highly impacted by lockdown, and number of hospitalizations per region, and moderately associated with socio-economic level of the region. Major cities largely shrank their pattern of connectivity, reducing it mainly to short-range commuting, despite the persistence of some long-range trips. Our findings indicate that lockdown was very effective in reducing population mobility across scales. Caution should be taken in the timing of policy announcements and implementation. Individual response to policy announcements may generate unexpected anomalous behaviors increasing the risk of geographical diffusion. On the other hand, risk awareness may be beneficial in further decreasing mobility in largely affected regions. Our findings help predicting how and where restrictions will be the most effective in reducing the mobility and mixing of the population, thus aiding tuning recommendations in the upcoming weeks, when phasing out lockdown.

INTRODUCTION

French authorities responded to the rapid growth of COVID-19 cases by imposing heavy restrictions on mobility, as many other countries in Europe and beyond[1]. Lockdown was enforced on March 17, 2020, and helped slow down infection rates and limit the strain on the healthcare system[2]. Accurately measuring changes in human mobility under these restrictions is essential to (i) quantitatively determine how imposed measures and recommendations (e.g. regarding telework where possible, ban of leisure trips) translated into reduced mobility at specific scales and times, (ii) inform models estimating the effectiveness of the ongoing lockdown in reducing the epidemic spread[3,4], (iii) help devising social distancing measures needed for the post-lockdown phase. Accessing human mobility data to measure these changes is now possible at several spatial and time scales, and often in nearly real-time. These data have been proven useful in many epidemiological contexts[5] – including for example the West Africa Ebola epidemic[6] – and are being used now for COVID-19 pandemic in many countries[7] – namely, Belgium[8], Germany[9], India[10], Italy[11,12], Poland[13], Spain[14], UK[15,16], USA[17–19].

Mobile phone records are one of the main sources of mobility data. They describe travel flows among the different locations of a country. These flows can be analyzed over time to study population patterns, with no information on individual users, safeguarding privacy[7,20,21]. In this report, we used data provided by Orange Business Service Flux Vision, and studied how mobility in France changed before and during lockdown. We broke down our results by trip distance, user age and residency, time of day, and analyzed regional data and spatial heterogeneities. We investigated behavioral responses to announcements of interventions, and to the epidemic burden, as well as associations of mobility reduction with demographic and socioeconomic indicators. Considering the network of travel connections among French locations, we also identified the most vulnerable and most resilient connections to the mobility shock induced by lockdown, with a specific focus on main French cities.

METHODS

Data. Mobile phone data were provided by the Orange Business Service Flux Vision. They comprised origin-destination travel volumes among ~1,500 geographic areas of mainland France, which group municipalities at the 2018 EPCI (Établissements Publics de Coopération Intercommunale) level. The average distance between the centroids of two adjacent areas is 22 km. Travel volumes were computed on-the-fly from signals exchanged between mobile phones and the mobile network, which contain information about the identifiers of the mobile phone and of the antenna handling the communication. Knowing the spatial localization of the antennas allows reconstructing the approximate position of the device in communication. This was then used to compute aggregated travel volumes among locations, with no residual information tracing back to the individual users. Data provided the number of displacements (or trips) observed between any two consecutive locations where the user spent at least 1 hour. For each pair of locations and any given day, data were provided stratified by age class. Travel flows were adjusted by Orange to be representative of the general population.

Regional hospitalization data were obtained from Santé publique France[22]. From them, we extracted as indicator the cumulated number of COVID-19-related hospitalizations per 100,000 inhabitants at a given date, for each region. On April 5, 2020, Grand-Est had the highest value (158.6), Bretagne the lowest (22.9). The sample standard deviation across regions was 44.3 hospitalizations per 100,000 inhabitants.

Population data and regional socioeconomic indicators were obtained from the French National Statistical Institute (INSEE)[23]. We used the following indicators: i) Fraction of population in the age range 24-59, corresponding with the peak of activity[24]. Île-de-France had the highest value (47.7%), Bourgogne had the lowest value (42.4%). The sample standard deviation across regions was 1.5%. ii) 90th percentile of the regional standard of living (*niveau de vie*), defined by INSEE[23] as the household's gross disposable income divided by the number of consumption units (measuring the size of the household – one unit for the first adult, 0.5 units for each additional person over 14 years of age and 0.3 for each child under 14 years of age). Île-de-France had the highest value (46,607 Euros), Hauts-de-France the lowest (33,548 Euros). The sample standard deviation across regions was 3,449 Euros.

Employment data were obtained from INSEE[25] and from the report of the French Ministry of Labor on the impact of restrictions on economic activities[26]. As indicator, we used the fraction of employees in the sectors mostly affected by lockdown. These are the sectors in which at least 50% of employees stopped working (hotels, hospitality, food services, and construction), or had been working remotely (finance, insurances, IT). Île-de-France had the highest value (22.91%), Bourgogne the lowest (11.70%). The sample standard deviation across regions was 3.10%.

Ethics. Mobile phone data were previously anonymized in compliance to strict privacy requirements, reviewed and approved by the French National Commission for Data Protection[27] (CNIL, Commission nationale de l'informatique et des libertés), ruling on all matters related to ethics, data, and privacy.

Timeline fit and prediction. To fit and forecast time series we used the forecasting procedure Prophet by Facebook Open Source[28]. We enforced weekly seasonality, and used school holidays by region[29] as additional (additive) regressors.

Trip analysis. Our analyses were performed on all trips and on trips whose geodesic distance between location centroids is longer than 100 km (*long trips*). The cutoff of 100 km effectively discards commuting, as ~95% of daily work-related trips are shorter than 100 km[30,31]. We distinguished between residents, i.e., users with French SIM cards, and foreigners. We broke down data in three age classes: young (younger than 18 y.o.), adults (18-64 y.o.), and seniors (65+ y.o.). We classified tips by their time of day: daytime (7am-7pm), nighttime (7pm-7am), and distinguished between weekdays and weekends. During weekdays we also considered rush hours (7am-9am, 5pm-7pm).

Mobility reduction during lockdown. Mobility reduction during lockdown was computed in a case-crossover framework by comparing the week starting Monday April 6, 2020 (3 weeks into lockdown), to the week starting Monday February 3 (control week). The latter was chosen as being before school holidays, and after strikes of public transport. All statistical analyses were performed in R, version 3.6.1. Two-sided significance of Pearson coefficients was determined at a level of 0.05.

Network analysis. Nodes in the networks represent the geographic locations in which we divided mainland France, and links represent trips between locations. Links are directed (trips have origins and destinations), weighted (by the number of trips linking two locations), and evolve in time. To handle and analyze networks we used standard Python libraries, among which networkx.

Maps. To smooth spatial data, we used a standard gaussian kernel with fixed characteristic distance, and adjusted locations by their population (see Appendix). The radius containing 95% of outgoing traffic from a city was computed by considering all mobility links that start from that city, each with its geodesic distance. They were included incrementally from the shortest to the longest (in terms of geodesic distance), until the cumulative sum of the weights of the included links reached 95% of the total outgoing traffic. Changes in circle radius capture changes in the geographic pattern of outgoing mobility. If mobility is reduced homogeneously across distances, the radius will remain constant. If reduction increases with the distance, the radius will decrease (and vice versa).

RESULTS

Timeline of COVID-19 epidemic in France. Three phases have marked the French response to COVID-19 epidemic (**Figure 1**). Phase 1 started in early January and can be identified with the first publication of COVID-19 case definition by Santé publique France[32] . Its aim was to detect imported cases as quickly as possible and conduct case-contact epidemiological investigations to identify possible local transmissions and isolate cases. Phase 2 started on February 29, 2020 upon appearance of localized clusters, and featured the same measures of Phase 1 coupled with targeted social distancing interventions (e.g. school closure, gatherings and public transport bans) to stop possible transmission in the community. During this phase, two clusters were identified, in Oise and Haute-Savoie. Phase 3 was declared on March 14 when the virus was recognized to actively circulate in the territory.

Starting few days before Phase 3, a set of announcements were made by French authorities that progressively led to the lockdown on March 17, 2020 (**Figure 1**): (i) March 12: announcement of school closure to be implemented starting March 16; (ii) March 14: announcement of closure of nonessential businesses with immediate effect; (iii) March 16: announcement of lockdown to be implemented the day after at noon; (iv) March 17: lockdown in effect.

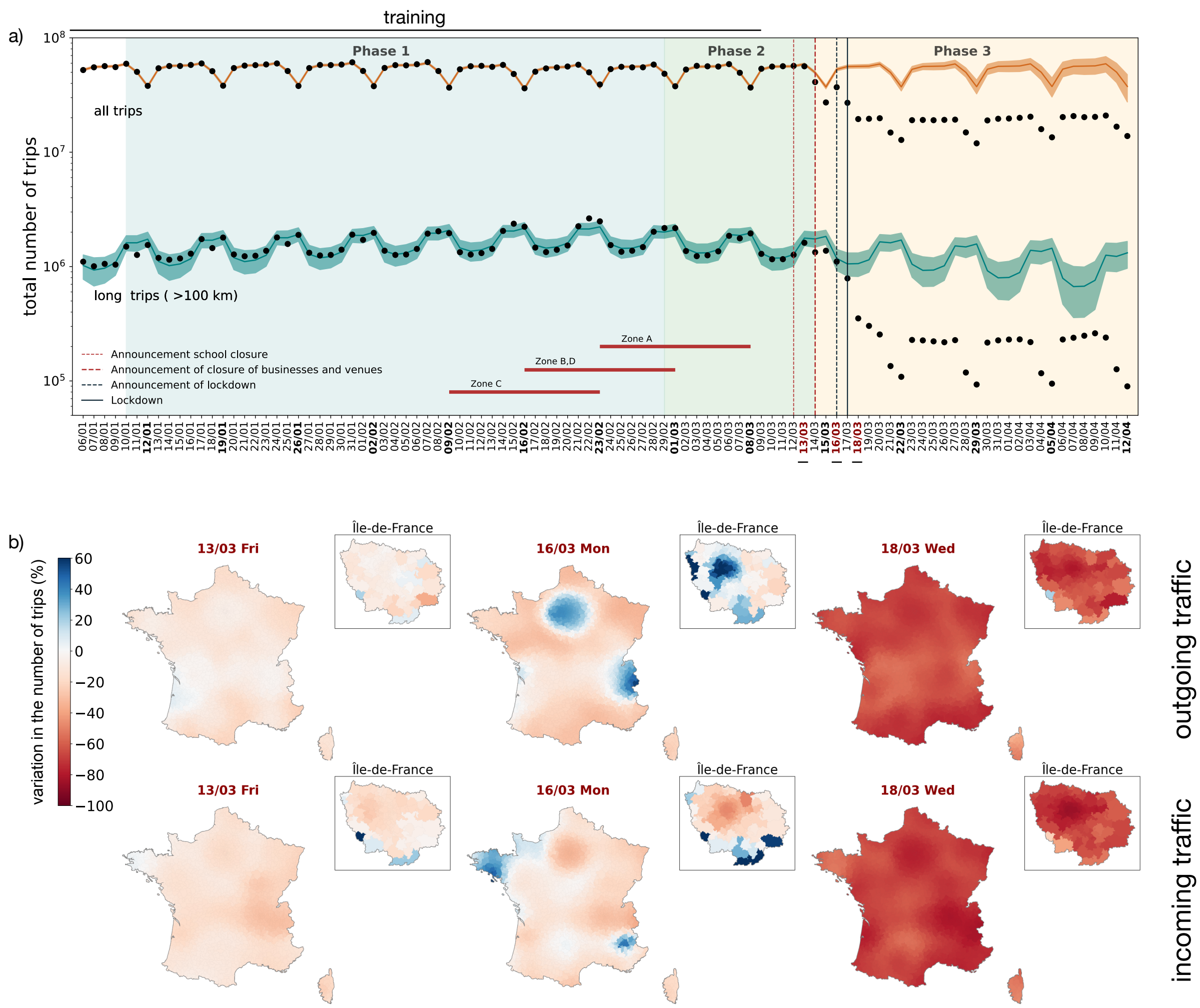

Figure 1. The phases of the COVID-19 epidemic in France, and its impact on mobility patterns. a) Colored areas correspond to the different phases of the epidemic response. Red lines mark main government interventions. Red horizontal thick lines indicate school holidays in the different areas of France (Paris is in zone C). The black dots track the evolution of the total number of daily trips measured from mobile phone data in France from January 6 to April 12. The top timeline considers all trips, the bottom timeline only long trips (>100 km). Each timeline is fitted (orange – all trips, green – long trips), with training set going from January 6 to March 9, and extrapolation up to April 12. Shaded areas represent 95% confidence intervals. b) Maps show the variation in traffic compared with the unperturbed baseline predicted by the fit. Top row: outgoing traffic; bottom row: incoming traffic. The chosen dates are March 13, March 16 (day before lockdown), March 18 (day after lockdown enforcement).

Behavioral response during the transition period up to lockdown implementation. While no observable change in mobility occurred during Phase 1 and 2 of the epidemic, the start of Phase 3 on March 14 had a substantial impact on mobility in France (**Fig. 1a**). This transition occurred prior to the announcement (March 16) and implementation (March 17) of lockdown measures, and saw nationwide mobility go from ~60M trips per day down to ~20M trips after lockdown entered into effect. The shock in mobility spread out over a transition period lasting almost a week.

To study in detail this transition, we quantified the deviation of measured traffic flows from the predicted evolution of traffic over time. Predictions were obtained from fitting mobility data from January 6, 2020, to Monday, March 9 (training set, **Fig. 1**), and assuming no perturbation due to COVID-19 and associated interventions after March 9.

Total flow was significantly below predictions starting March 14, as a likely consequence of the start of Phase 3. Mobility further decreased on Sunday, March 15, when local elections took place. Instead, an anomalous rise in traffic took place on the day before lockdown enforcement, which had higher volume than the surrounding days, whereas still lower than the predicted baseline. Long trips (>100 km) were also significantly – albeit slightly - below the predicted baseline during the weekend (March 14, 15). They however went back to seemingly normal values on March 16 – i.e., in agreement with the unperturbed prediction -, and near-to-normal values on lockdown day. However, this country-level behavior hid anomalous deviations from the predicted mobility behavior in specific locations, as **Fig. 1b** shows. Spikes in outgoing traffic are distinctively visible in Île-de-France (the region of Paris) and, at the same time, in incoming traffic in Normandy and Bretagne. They measure the pre-lockdown exodus out of Paris occurring before lockdown took effect[33,34]. Analyses at finer scales within Île-de-France revealed that anomalous outgoing traffic concentrated in the Paris area, and western Île-de-France. Similar spikes of outgoing and incoming traffic were also visible in the South East, close to the Alps, as reported previously[33].

The transition starting with Phase 3 reshaped weekly patterns compared to those measured in the unperturbed mobility. Before the mobility shock, a stable weekly pattern was observed, with peaks on Fridays and troughs on Sundays for all trips, and peaks on both Fridays and Sundays for long trips. During the transition, no weekly pattern was recognizable, as mobility was perturbed in different ways across several days. Following the transition, patterns no longer featured peaks in mobility on Fridays (for all trips) or on Sundays (for long trips).

Mobility during lockdown. Mobility patterns quickly entered a new equilibrium after lockdown enforcement, marking the end of the transition period. Using a crossover framework (see Methods), we found that lockdown decreased the overall number of trips by 65% (**Figure 2a**). Reduction was stronger for trips made by foreigners (~85%), suggesting that the enforcement of lockdown disrupted tourism and impacted more the mobility of foreign nationals in the country[35]. Their number of trips was however very small even before lockdown compared to French residents (3%), therefore we excluded them from the rest of the analysis as their contribution is negligible. Long-range traffic (>100 km) was disrupted more severely than average (85% reduction, **Fig. 2a**). This was likely associated with a disruption of long-range transportation (trains, flights), and the ban of leisure-related trips, also confirmed by the almost disappearance of long trips during the weekend (see below).

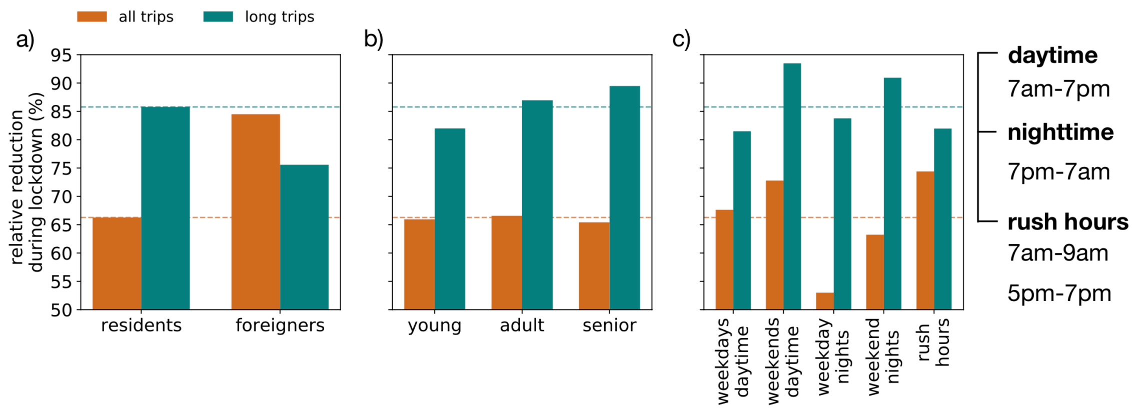

Figure 2. Mobility reduction during lockdown across user type, age and time of day. Reduction is computed as the average over the week starting Monday April 6, with respect to the average over the first week of February (starting Monday February 3). a), b) and c) show the relative reduction broken down by residents/foreigners, age classes, and times of the day. They also show statistics for all trips (orange) and long trips (green), defined as trips with geodesic distance longer than 100 km. Horizontal orange and green lines indicate relative reduction on all residents (all, long, respectively).

Mobility reduction in total trips was homogeneously distributed across age classes (**Fig. 2b**). When considering only long trips, reduction instead increased with age, as seniors reduced their trips above 100 km by ~ 90%.

Drops in mobility were uneven across the time of the day (**Fig. 2c**). Movements during rush hours were the most disrupted, indicating that the combined effect of school closure and telework led to a ~75% reduction. Daytime movements during weekends also exhibited a higher-than-average decrease, hinting at a successful reduction of recreational activities. Nighttime movements during weekdays instead recorded the lowest reduction, well below average. They might be related to unavoidable work-related mobility, whose impact is however likely to be limited, as these movements make up for only ¼ of the total. Long-range mobility almost completely stopped during weekends (around 95% decrease).

Regional heterogeneities in mobility reduction during lockdown. Traffic reductions were not homogeneous across the 13 regions of mainland France. Reduction of internal traffic was above average in 4 regions (Île-de-France, Auvergne-Rhône-Alpes, Grand Est, Provence-Alpes-Côte d'Azur), whereas markedly below average in Bourgogne-Franche-Comté, Centre-Val de Loire, and Normandy (**Figure 3**). Similar fluctuations were visible in outgoing traffic (coefficient of variation equal to 8.4% compared to 8.0% for internal traffic). Île-de-France, Hauts-de-France and Grand Est all experienced above-average reductions in outgoing mobility, as high as 80% for Île-de-France. Corse also exhibited a reduction comparable to Île-de-France, showing a clear disruption of the long-range connections linking the island to mainland France. Similar reductions were obtained with incoming fluxes in the regions (not shown).

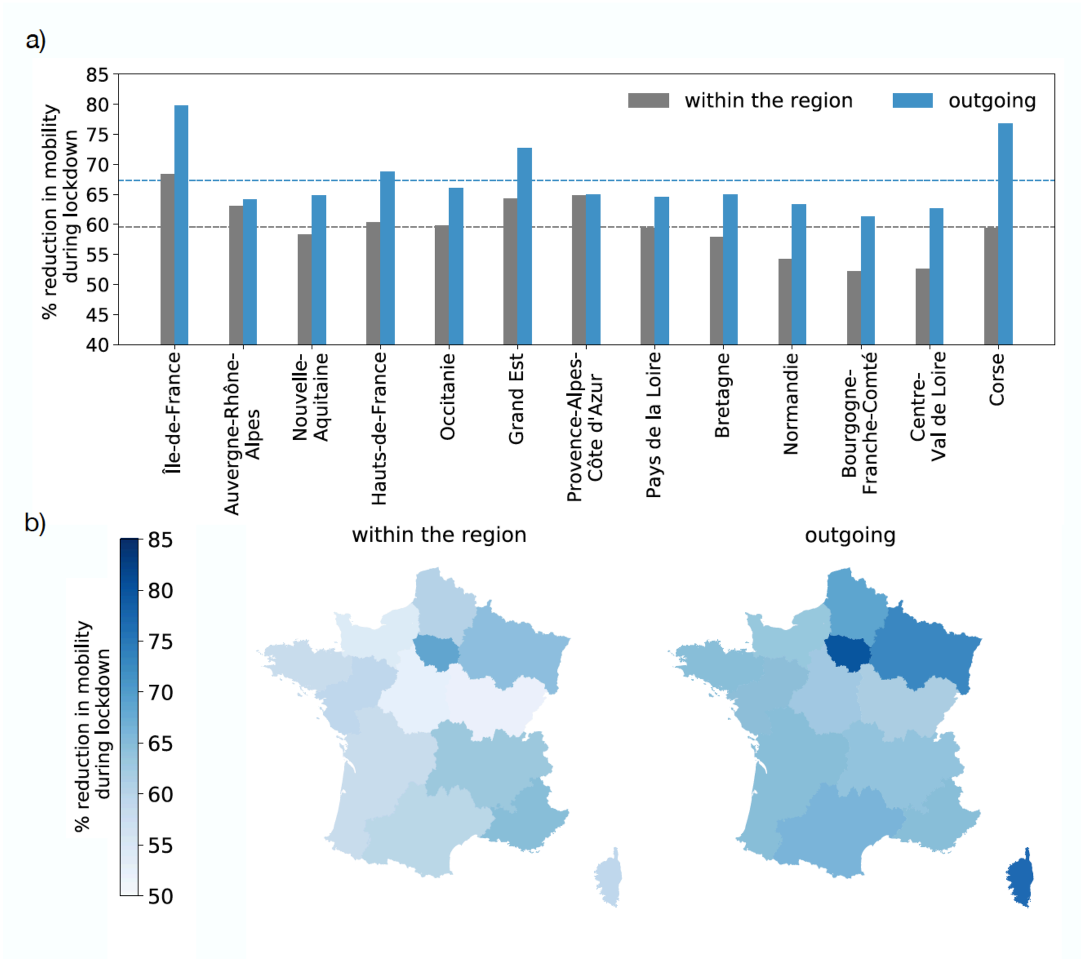

Figure 3. Lockdown-induced mobility reduction across regions. a) Breakdown of mobility reduction by region in mainland France. Reductions for trips within region are in gray, for trips leaving the region are in blue. The horizontal gray and blue lines indicate the corresponding averages across regions. b) Map visualization of a).

The impact of nationwide lockdown in the reduction of outgoing mobility per region was strongly associated with the fraction of the population in the most active age range (24-59 y.o.)[24] (Pearson r = 0.91, p < 0.01) and the fraction of workers employed in sectors that substantially modified their organization during lockdown, due to telework, partial or full closure of activities (Pearson r = 0.80, p < 0.01) (**Table 1** and **Figure 4**). It was moderately associated with the standard of living of the region (Pearson r = 0.63, p = 0.02).

Regional drops in mobility in a given week (April 6-12, 2020) were strongly associated with COVID-19 hospitalization rates registered and communicated in the week before (April 5) (Pearson r = 0.73, p < 0.01; **Figure 4**).

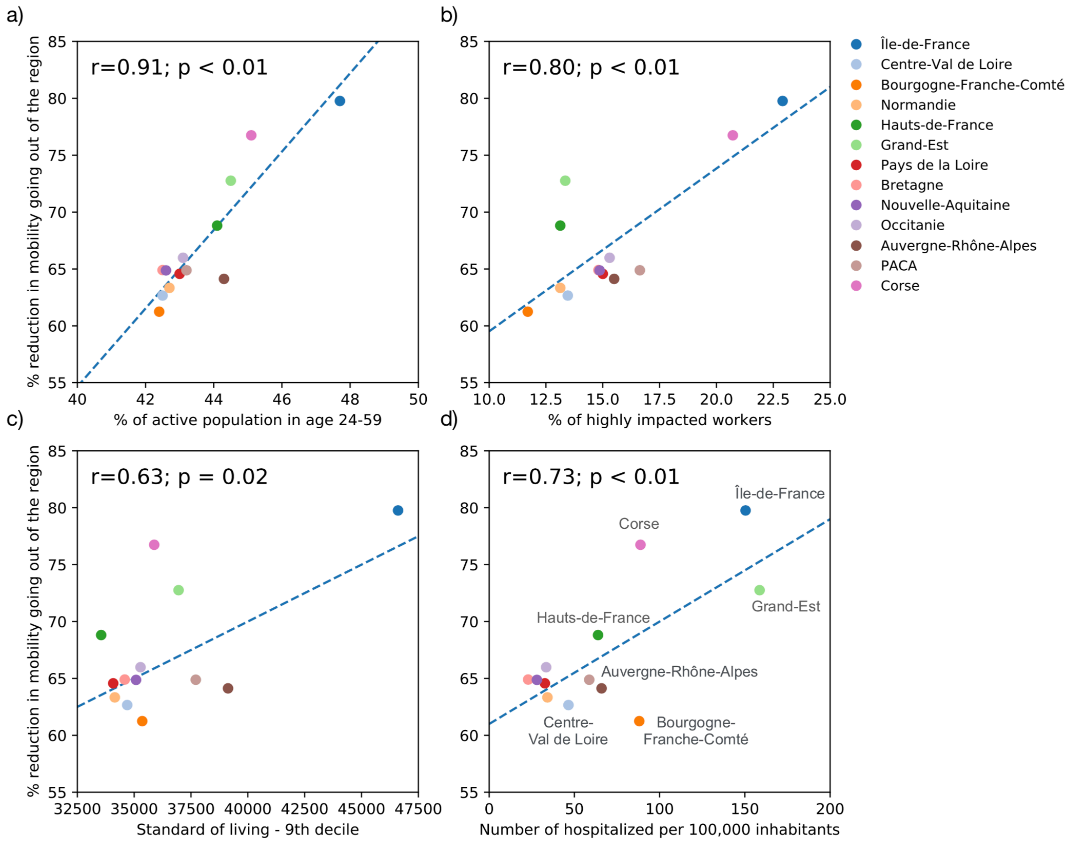

Figure 4. Reduction in outgoing mobility for the week April 6-12, 2020 vs. epidemic, socio-economic, and demographic indicators. Correlation is evaluated between outgoing traffic and the four considered indicators: a) the population in active age (24-59 years old), b) the fraction of employees in the sectors mostly affected by lockdown. c) the 90th percentile of the regional standard of living[23], d) the cumulated number of COVID-19 hospitalizations per 100,000 inhabitants on April 05, 2020. Pearson correlation coefficients and their p-values are reported.

Similar results were obtained for drops in mobility within the region, except for the association with the hospitalization rate per region, which however showed a similar, though non-significant, tendency (**Table S1** and **Fig. S1** in **Appendix**). Taking out the data point of Île-de-France as the region mostly affected by a departure of inhabitants for relocation in other regions led to similar results (**Table S2** in **Appendix**).

Disruption of mobility connections. Shifting the focus from overall traffic reductions to mobility connections between locations, we found that some connections completely disappeared, as individuals stopped going from one location to another (**Figure 5**).

The probability that a mobility connection observed in the control week (week of February 3, 2020) was also observed when interventions were announced and after they entered into effect (persistence probability, **Fig. 5b**) decreased steadily during the transition period (67% of connections surviving in the week of school closure and non-essential activity closure announcements, March 9 to 15; 50% in the week of announcement and implementation of lockdown, March 16 to 22) to stabilize in the first full week of lockdown (34% of connections surviving, March 23) and beyond. Long connections were less resilient than average, as only 1/4 of them survived lockdown.

After lockdown effects stabilized (e.g. starting the second full week of lockdown, March 30), connections usually characterized by small traffic prior to restrictions (weak connections) were the most likely to disappear, with 70% of them corresponding to 100 trips per week (**Fig. 5c**). The traffic lost on these connections however barely contributed to total traffic reduction (3% contribution). Restricting the analysis to long mobility connections (> 100 km), the fraction of the weak connections disappearing slightly increased (from 70% to 89%), however with a reduction of 47% of the traffic.

The disruption in connections occurred with a certain delay compared to reductions in traffic. For example, on Monday March 16 – the day before lockdown – traffic was reduced by 30% with respect to the previous Monday, but the number of connections went down by 4% only. One week after (March 23), traffic drop was 64% and the drop in the number of connections was 55%.

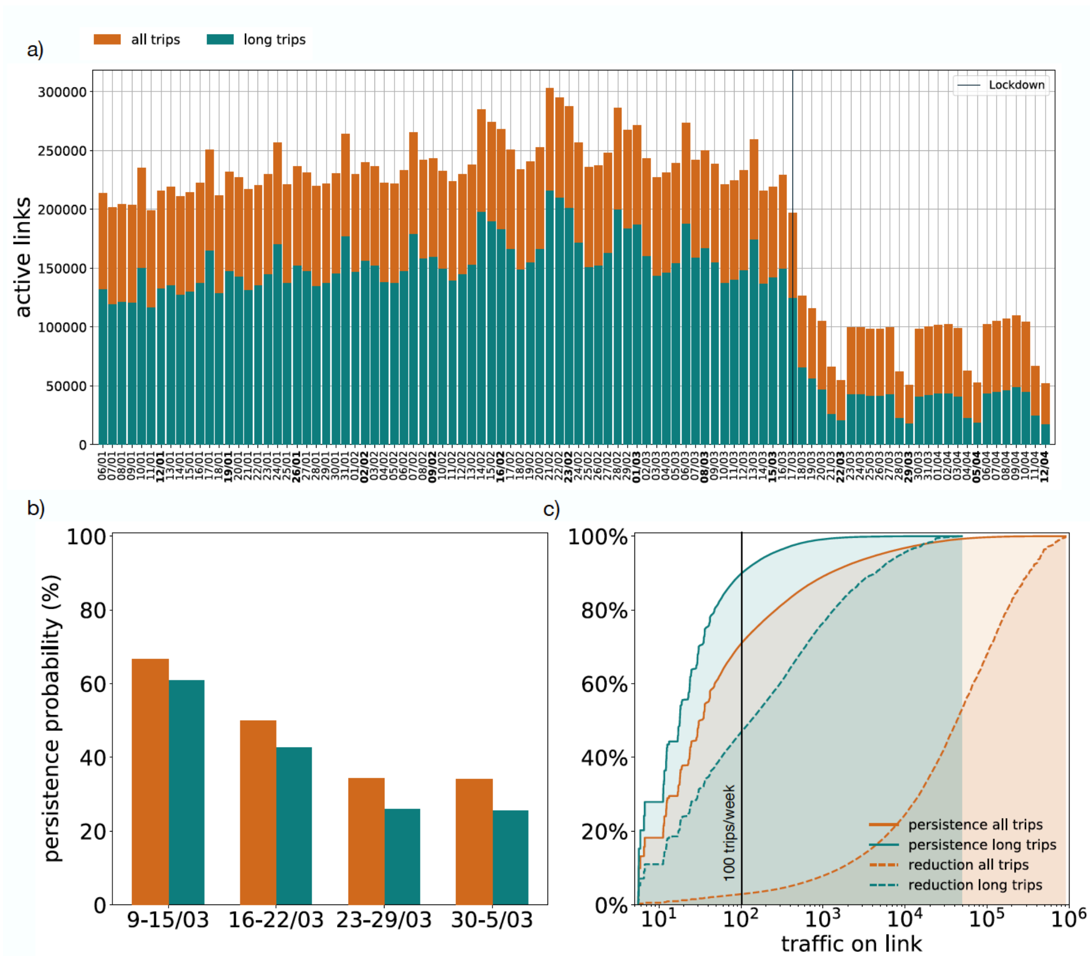

Figure 5. Network analysis. a) Number of mobility connections between French locations over time. b) Link persistence probability: probability that a connection present during week February 3-9 is still present in one of the four selected weeks: before lockdown (March 9-15), during enforcement (March 16-22), during lockdown (March 23-29, March 30 – April 5). c) Persistence probability and traffic reduction in relation with traffic. For a given x-axis value (traffic on link), solid lines measure the fraction of broken links which used to have at most that weight in the baseline week. Dashed lines report the fraction of missing traffic that was

lost on connections which used to have at most a certain weight in the baseline week. For all panels: orange: all links, green long links (longer than 100 km).

Mobility connections of 10 most populated French cities.

Restrictions on mobility during lockdown had an uneven impact on the 10 most populated French cities. The circle containing 95% of outgoing traffic from each city decreased after lockdown took effect for all cities, indicating that long-range mobility was disrupted more than short-range one (**Figure 6**). But reductions varied from more than 80% (Paris, Bordeaux, Nice) to 60% (Strasbourg, Lille), mainly due to different patterns of commuting and connectivity characterizing the mobility of each city. In normal circumstances, Paris is connected to almost the rest of the country, whereas the other cities have a more localized pattern of mobility with fewer long-range connections. Once lockdown was implemented, surviving mobility shrank around the cities.

Connections among main cities disappeared too. Considering the 4 connections per city with highest traffic that are compromised by the lockdown, we no longer detected mobility from Bordeaux, Montpellier, and Nantes to Lyon, or from Montpellier to Strasbourg (**Figure 6**), compared to pre-emergency situation.

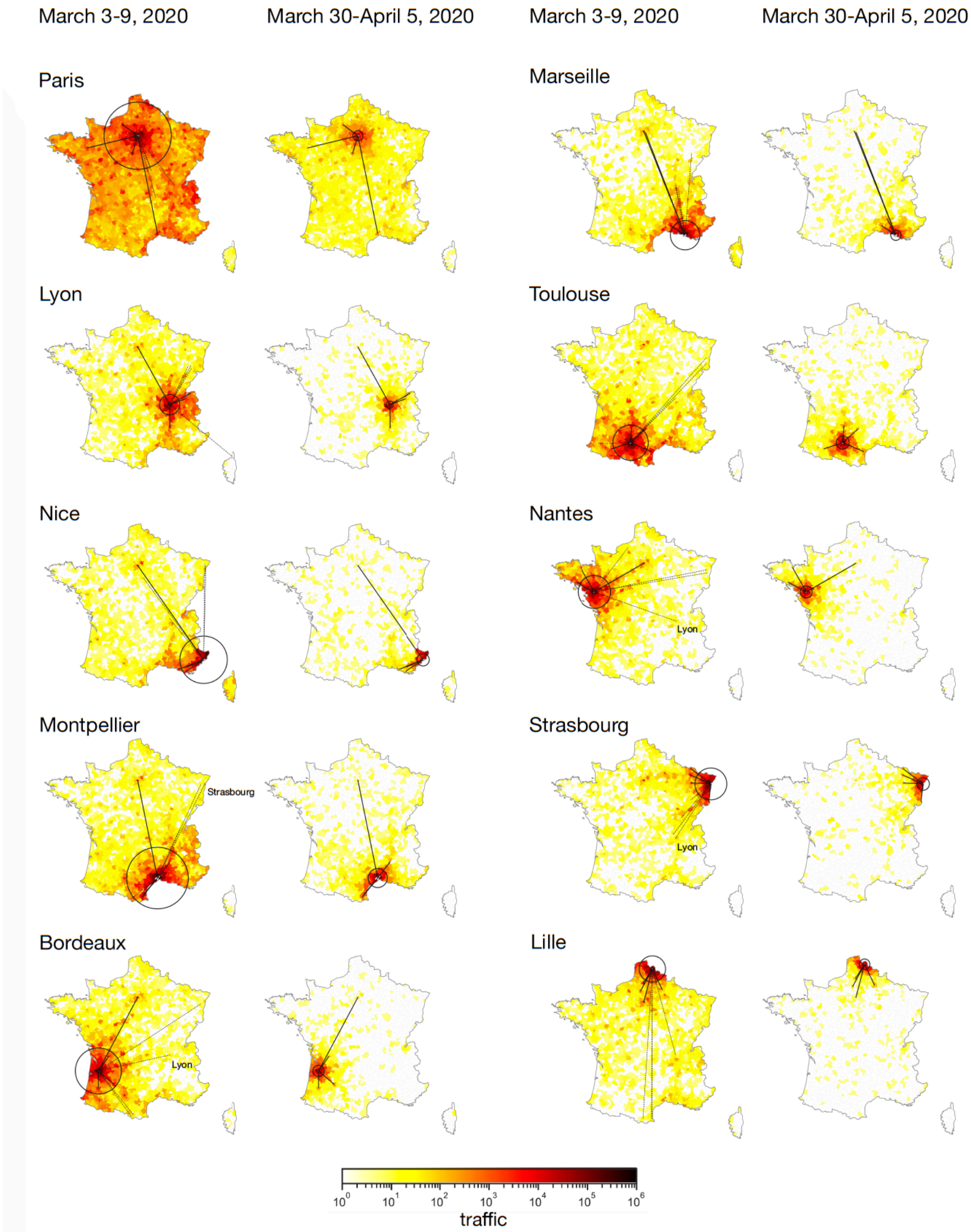

Figure 6. Outgoing egocentric networks of the 10 most populated cities in France during baseline week (starting Feb 3) and during lockdown week starting March 30. Locations are colored by incoming traffic from the selected city. Solid lines indicate links that persist during lockdown. Dashed lines link that disappear. Both are selected to be the top ranking by traffic during the baseline week. The circles contain 95% of the outgoing traffic.

DISCUSSION

Using travel flow data extracted from mobile phone trajectories, we documented a large drop in both short-range and long-range population mobility following lockdown enforcement in France. Overall, trips were reduced by 65%, similarly to reductions found in Belgium[8], Spain[14], and Italy[11] during lockdown, albeit different data sources, spatial resolutions, and definitions of mobility proxies prevent direct numerical comparisons.

The transition signaling the drop in mobility lasted almost a week, anticipating the enforcement of lockdown and creating opposite mobility behaviors. Individuals started spontaneously reducing their mobility on Saturday following the announcement of school closure, likely because of fear of the growing epidemic and heightened risk awareness[36–40] generated by the first governmental decision on nationwide interventions. The weekday-to-weekend pattern was disrupted, with overall mobility on Monday following the closure of all non-essential activities similar to the preceding Saturday. At the same time, fear of an imminent change in policy imposing stricter restrictions – as already implemented in Italy, Spain, Austria[41] pushed individuals to relocate themselves even to farther away regions where to spend the period of lockdown, if put in place. The exodus, largely covered by the press [33,34], occurred already before the announcement of lockdown and led to anomalous increases in mobility flows out of certain regions (e.g. Île-de-France) and incoming in others (e.g. Normandy). Such behavior was similarly reported in China (from Wuhan to other regions), in Italy (from the North to the South) prior to the implementation of lockdown, and in India[10]. It demonstrates that the timing at which a policy is announced might disrupt social dynamics as much as the direct effect of the policy, at least in the short term. Increased caution should therefore be considered in the period from announcements to enforcement to avoid unpredictable behaviors that may result in unwanted seeding of the epidemic to other areas. No increase in viral circulation became then visible in the receiving regions in the following weeks, as lockdown strongly suppressed epidemic activity in all regions[3,4,42,43]. Seeding events due to relocations may however become more important in phasing out the lockdown, as less strict social distancing measures may prevent such suppression. Region-specific interventions may increase this risk by inducing similar behavioral responses. New York State reported for instance increased mobility in counties with no imposed lockdown[19]. In this perspective, nationwide interventions and restrictions limiting displacements were adopted by several countries[44,45] to prevent compensation effects and reduce the possible geographical spread of the epidemic.

Once lockdown entered into effect, population mobility reductions were heterogeneous across regions. Larger reductions were measured in regions more severely hit by the epidemic, with an estimated 1% decrease in regional mobility every 10 additional hospitalizations (per 100,000 inhabitants). This suggests that individuals witnessing a larger COVID-19 burden on the hospital system in their region may have further limited displacements compared to those living in less affected regions. Media largely communicated on the epidemic, also providing early on region-specific information on hospitalizations and mounting pressure on the healthcare system. Exposure to this information likely triggered a behavioral response increasing compliance to movement restrictions. A similar, though stronger, behavior was observed during a 3-day national lockdown enforced nationwide in Sierra Leone in March 2015 in an effort to control Ebola epidemic[6]. The correlation remains significant even taking out the region of Île-de-France, which experienced a reduction in population due to relocation of individuals.

Clearly, other factors may have come into play to differentiate drops in regional mobility. Lockdown restrictions had a severe impact on jobs and the organization of work. Regions with the higher proportion of activity sectors mostly impacted by the lockdown (due to telework, but also to complete or partial closure of sectors, such as tourism, entertainment, food services, and construction) also experienced larger drops on mobility. A smaller fraction of active individuals continued to go to work, while the others limited their displacements respecting lockdown mobility restrictions. Indeed, regions with larger portions of the population in the most active age range (24-59y)[1,2] were also the ones where lockdown had the largest effects. Besides the displacements to go to work, active population is also highly mobile for leisure activities, which were completely banned by restrictions (with short exceptions to do sport once a day for at most 1 hour).

Uneven mobility drops were also associated with socioeconomic disparities. Increasing evidence points at different socioeconomic strata getting uneven shares of the COVID-19 burden[46]. Higher income jobs can often be performed remotely, in confinement, whereas lower income jobs cannot. A survey in France reported that 39% of low income workers were still going to their workplace during lockdown, against only 17% of high income workers[47]. Also, wealthier population strata weather short-term financial losses better, making them more prone to stop working and stay at home if they are afraid or sick. At the same time, they can afford more leisure activities and have a more varied social network[48,49], leading to a higher rate of leisure-related mobility in normal circumstances. Wealthier populations then likely experienced a larger mobility reduction because of the possibility to work remotely or stop working, as well as for the imposed ban on leisure activities.

A strong response was documented in the older age class, which is at highest risk of developing severe forms of COVID-19 if infected. Seniors almost stopped taking trips longer than 100 km, likely to avoid leisure activities and family trips, as recommended by authorities. The most effective reduction in overall mobility occurred during rush hours, associated with a disruption of commuting patterns. This reduction alone likely boosted the role of mobility restrictions in suppressing viral diffusion, as mounting evidence shows that public transportation is a main risk factor for transmission[50,51].

Lockdown had a different impact on mobility depending on distance, causing larger disruptions on long-range mobility, as also reported in Belgium[8] and Italy[11]. Short-range and long-range mobility flows play different roles in the spread of an infectious disease epidemic. Short-range connections are mainly responsible for local diffusion in the community within and around a metropolitan area, whereas long-range connections drive the spatial spread of the epidemic, acting as seeding events to otherwise unaffected or weakly affected areas[52]. Mobility flows out of the city of Wuhan were shown to have seeded other prefectures in China in the early phase of the epidemic before travel restrictions and substantial control measures were implemented[53–55] . A delayed response or less efficient lockdown would have likely led to a larger outbreak increasing its geographical range. Coupled with social distancing interventions, long-range mobility restrictions are therefore critical to geographically contain the epidemic, especially when epidemic activity is largely heterogeneous at the spatial scale, showing a patchy geographical pattern observed in many affected countries including France. Banning trips above 100 km as announced by French authorities[44] will continue breaking the spreading pathways along which the epidemic could spread and reducing the locations reachable by the virus, as observed during the lockdown. Nonetheless, in the lockdown phase we documented that some long-range mobility connection, among the ones with highest traffic, survived the restrictions – namely, from Paris to

Montpellier, and from the other most populated cities to Paris (except Toulouse and Strasbourg). These movements should be carefully accompanied by strict hygienic and preventive measures to avoid re-seeding events from visitors or returning residents, as discussed above.

The largest reduction of mobility across distance was reported for Paris. Before lockdown, 95% of outgoing traffic reached destinations within 200 km from the city center, approximately the distance between Paris and Lille, close to the Belgian border. After lockdown, this radius reduced to 29 km, the distance from the city center to Disneyland Paris. Achievable distances from large cities shrank during lockdown, even in absence of explicit limitations on distance, also reducing the number of reachable destinations. Mobility became more localized and restructured around metropolitan areas, serving the needs of individuals who continued their daily displacements associated to work, e.g. in essential professional categories. A similar geographical fragmentation induced by restructured local job markets was also observed in Italy[12] .

Our analysis offered plausible interpretations on how the labor market, demographic and socio-economic indicators, and awareness of increased epidemic risk might have shaped the reduction in mobility, confirming evidence observed in previous[6,37] and current[47,56] outbreaks. Being observational in nature, the study does not allow us to identify causal relationships; also, confounding effects among the covariates may be expected, but the available sample was too small to take this into account. Focusing on the reduction in mobility during lockdown and its association to hospitalizations in the same time period, our study did not aim to assess the role of mobility in shaping the epidemic spread, but to investigate a behavioral response likely induced by risk awareness. Associations were robust also removing the data point for Île-de-France, the region mostly affected by the exodus of individuals relocating in other locations. This suggests that associations are not biased by a change in population size of the region. Regional variations in mobility may be induced by differential restrictions based on estimated epidemic activity in the region[10]. However, this was not the case in France, where a nationwide lockdown was applied uniformly in the country. Local authorities additionally imposed heavier restrictions in certain areas over time, like curfews in cities in Hauts-de-France and in the south of France[57]. We did not consider these additional restrictions as possible factors in our analysis. We expect them to result in smaller effects, likely not visible at the resolution scale under study here.

Using aggregated flow data extracted from mobile phone trajectories, we documented the large impact that lockdown had on reducing mobility in France. Different effects were observed across scales, with larger disruptions on long-range connections leading to a localization of the mobility. Factors related to demography, professional categories, and socio-economic level were all associated with the reduction in mobility. Uneven drops in population movements by region may also be explained by a different behavioral response linked to the perceived risk of the epidemic in the region. Our findings may help predicting how and where restrictions will be the most effective in reducing the mobility and mixing of the population, thus aiding tuning recommendations in the upcoming weeks, when phasing out lockdown.

ACKNOWLEDGMENTS

This study is partially funded by: ANR projects EVALCOVID-19 (ANR-20-COVI-0007), SPHINX (ANR-17-CE36-0008-05) and DATAREDUX (ANR-19-CE46-0008-03); EU H2020 grants RECOVER (H2020- 101003589) and MOOD (H2020-874850); REACTing COVID-19 modeling grant. We thank Luca Ferreri, Sylvain Bourgeois, Erwan Le Quentrec, Zbigniew Smoreda, Chiara Poletto, Pierre-Yves Boëlle for useful discussions.

REFERENCES

1. Anderson, R. M., Heesterbeek, H., Klinkenberg, D. & Hollingsworth, T. D. How will country-based mitigation measures influence the course of the COVID-19 epidemic? *The Lancet* **395**, 931–934 (2020).
2. santepubliquefrance.fr. COVID-19 : point épidémiologique du 16 avril 2020. https://www.santepubliquefrance.fr/maladies-et-traumatismes/maladies-et-infections-respiratoires/infection-a-coronavirus/documents/bulletin-national/covid-19-point-epidemiologique-du-16-avril-2020.
3. Di Domenico, L., Pullano, G., Sabbatini, C. E., Boëlle, P.-Y. & Colizza, V. Expected impact of reopening schools after lockdown on COVID-19 epidemic in Île-de-France. Epicx-Lab Rep. 10 (2020). 21.
4. Di Domenico, L., Pullano, G., Sabbatini, C. E., Boëlle, P.-Y. & Colizza, V. Expected impact of lockdown in Île-de-France and possible exit strategies. *medRxiv* 2020.04.13.20063933 (2020).
5. Barbosa, H. *et al.* Human mobility: Models and applications. *Phys. Rep.* **734**, 1–74 (2018).
6. Peak, C. M. *et al.* Population mobility reductions associated with travel restrictions during the Ebola epidemic in Sierra Leone: use of mobile phone data. *Int. J. Epidemiol.* **47**, 1562–1570 (2018).
7. Oliver, N. *et al.* Mobile phone data and COVID-19: Missing an opportunity? *ArXiv200312347 Cs* (2020).
8. Covid-19: belgium analyses telecom data to measure the impact of confinement. https://press.telenet.be/covid-19-belgium-analyses-telecom-data-to-measure-the-impact-of-confinement#.
9. Brockmann, D. et al. Covid-19 Mobility Project in Germany. http://rocs.hu-berlin.de/covid-19-mobility/.
10. Denis, E., Telle, O. & Benkimoun, S. Mapping the lockdown effects in India: how geographers can contribute to tackle Covid-19 diffusion. *The Conversation* http://theconversation.com/mapping-the-lockdown-effects-in-india-how-geographers-can-contribute-to-tackle-covid-19-diffusion-136323.
11. Pepe, E. *et al.* COVID-19 outbreak response: first assessment of mobility changes in Italy following lockdown. (2020).
12. Bonato, P. *et al.* Mobile phone data analytics against the COVID-19 epidemics in Italy: flow diversity and local job markets during the national lockdown. *ArXiv200411278 Cs Stat* (2020).
13. Statista. Community mobility changes due to the coronavirus (COVID-19) outbreak in Poland. https://www.statista.com/statistics/1110080/poland-mobility-changes-due-to-covid-19/.
14. José Javier Ramasco, M. M. 4° Informe sobre los cambios de movilidad en España debido a las medidas de confinamiento contra la extensión del COVID-19.

15. Qian, M. et al. Oxford COVID-19 Impact Monitor: https://www.oxford-covid-19.com/. https://www.oxford-covid-19.com/.
16. Santana, C., Botta, F., Barbosa, H., Privitera, F. & Clemente, R. D. Analysis of human mobility in the UK during the COVID-19 pandemic. 7.
17. Klein, B. *et al.* Assessing changes in commuting and individual mobility in major metropolitan areas in the United States during the COVID-19 outbreak. 29.
18. Bakker, M., Berke, A., Groh, M., Pentland, S. & Moro, E. Effect of social distancing measures in the New York City metropolitan area. 16.
19. Gao, S., Rao, J., Kang, Y., Liang, Y. & Kruse, J. *Mapping County-Level Mobility Pattern Changes in the United States in Response to COVID-19*. https://papers.ssrn.com/abstract=3570145 (2020) doi:10.2139/ssrn.3570145.
20. Buckee, C. O. Protect privacy of mobile data. *Nature* **514**, 35–35 (2014).
21. Buckee, C. O. *et al.* Aggregated mobility data could help fight COVID-19. *Science* **368**, 145 (2020).
22. santepubliquefrance.fr. Indicateurs : cartes, données et graphiqueshttps://geodes.santepubliquefrance.fr/#c=indicator&f=0&i=covid_hospit.hosp&s=2020-04-09&t=a01&view=map1.
23. INSEE. https://www.insee.fr.
24. INSEE. Tableaux de l'économie française. https://www.insee.fr/fr/statistiques/3676623?sommaire=3696937.
25. INSEE. Bilans économiques 2018 des régions françaises. https://www.insee.fr/fr/information/4166862.
26. DARES. Activité et conditions d'emploi de la main-d'œuvre pendant la crise sanitaire Covid-19. https://dares.travail-emploi.gouv.fr/IMG/pdf/dares_acemo_covid19_synthese_17-04-2020.pdf.
27. CNIL. https://www.cnil.fr/.
28. Prophet. https://facebook.github.io/prophet/.
29. education.gouv.fr. https://www.education.gouv.fr/calendrier-scolaire-100148.
30. INSEE. Mobilités professionnelles en 2015. https://www.insee.fr/fr/statistiques/3566477.
31. INSEE. Mobilités scolaires en 2015. https://www.insee.fr/fr/statistiques/3566470.
32. santepubliquefrance.fr. Surveillance épidémiologique du COVID-19. https://www.santepubliquefrance.fr/presse/2020/surveillance-epidemiologique-du-covid-19.
33. Le Figaro. Coronavirus : le grand exode des citadins. https://www.lefigaro.fr/secteur/high-tech/le-grand-exode-des-citadins-20200327.
34. Le Monde. Confinement : plus d'un million de Franciliens ont quitté la région parisienne en une semaine. https://www.lemonde.fr/pixels/article/2020/03/26/confinement-plus-d-un-million-de-franciliens-ont-quitte-la-region-parisienne-en-une-semaine_6034568_4408996.html.
35. CNEWS. Coronavirus : quel impact sur le tourisme. https://www.cnews.fr/conso/2020-03-11/coronavirus-quel-impact-sur-le-tourisme-935096.
36. Donnelly, C. A. *et al.* Epidemiological determinants of spread of causal agent of severe acute respiratory syndrome in Hong Kong. *The Lancet* **361**, 1761–1766 (2003).
37. Odlum, M. & Yoon, S. What can we learn about the Ebola outbreak from tweets? *Am. J. Infect. Control* **43**, 563–571 (2015).

38. Liu, S., Yao, C., Zhang, J., Su, J. & Lin, G. Outpatients' behavior of seeking medical care after onset of severe acute respiratory syndrome and community control measures in Beijing. *Asia Pac. Fam. Med.* **4**, (2005).
39. Rubin, G. J., Amlôt, R., Page, L. & Wessely, S. Public perceptions, anxiety, and behaviour change in relation to the swine flu outbreak: cross sectional telephone survey. *BMJ* **339**, (2009).
40. Rizzo, C. *et al.* Survey on the Likely Behavioural Changes of the General Public in Four European Countries During the 2009/2010 Pandemic. in *Modeling the Interplay Between Human Behavior and the Spread of Infectious Diseases* (eds. Manfredi, P. & D'Onofrio, A.) 23–41 (Springer, 2013). doi:10.1007/978-1-4614-5474-8_2.
41. Epicentre. COVID-19 Epi Dashboard. https://reports.msf.net/public/covid19/.
42. Salje, H. *et al.* Estimating the burden of SARS-CoV-2 in France. *medRxiv* 2020.04.20.20072413 (2020) doi:10.1101/2020.04.20.20072413.
43. Roux, J., Massonnaud, C. & Crépey, P. COVID-19: One-month impact of the French lockdown on the epidemic burden. *medRxiv* 2020.04.22.20075705 (2020) doi:10.1101/2020.04.22.20075705.
44. gouvernement.fr. Stratégie de déconfinement. https://www.gouvernement.fr/info-coronavirus/strategie-de-deconfinement.
45. governo.it. "Fase 2". http://www.governo.it/it/faq-fasedue.
46. The Economist. American inequality meets covid-19. https://www.economist.com/united-states/2020/04/18/american-inequality-meets-covid-19.
47. Chloé Morin, Jérôme Fourquet, Marie Le Vern. Premiers de corvée et premiers de cordée, quel avenir pour le travail déconfiné ?. https://jean-jaures.org/nos-productions/premiers-de-corvee-et-premiers-de-cordee-quel-avenir-pour-le-travail-deconfine.
48. Eagle, N., Macy, M. & Claxton, R. Network diversity and economic development. *Science* **328**, 1029–1031 (2010).
49. Pappalardo, L., Pedreschi, D., Smoreda, Z. & Giannotti, F. Using big data to study the link between human mobility and socio-economic development. in *2015 IEEE International Conference on Big Data (Big Data)* 871–878 (2015). doi:10.1109/BigData.2015.7363835.
50. Harris, J. E. The Subways Seeded the Massive Coronavirus Epidemic in New York City. 22.
51. Bi, Q. *et al.* Epidemiology and transmission of COVID-19 in 391 cases and 1286 of their close contacts in Shenzhen, China: a retrospective cohort study. *Lancet Infect. Dis.* **0**, (2020).
52. Balcan, D. *et al.* Multiscale mobility networks and the spatial spreading of infectious diseases. *Proc. Natl. Acad. Sci.* **106**, 21484–21489 (2009).
53. Jia, J. *et al.* Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature* 1–11 (2020) doi:10.1038/s41586-020-2284-y.
54. Kraemer, M. *et al. The effect of human mobility and control measures on the COVID-19 epidemic in China*. (2020). doi:10.1101/2020.03.02.20026708.
55. Lai, S. *et al.* Effect of non-pharmaceutical interventions to contain COVID-19 in China. *Nature* (2020) doi:10.1038/s41586-020-2293-x.
56. The New York Times. Location Data Says It All: Staying at Home During Coronavirus Is a Luxury. https://www.nytimes.com/interactive/2020/04/03/us/coronavirus-stay-home-rich-poor.html.

57. Le Monde. Coronavirus : le casse-tête juridique du couvre-feu. https://www.lemonde.fr/politique/article/2020/04/01/coronavirus-le-casse-tete-juridique-du-couvre-feu_6035172_823448.html. *Le Monde.fr* (2020).

APPENDIX

Spatial smoothing

Let x_i be the value in location i of the quantity we want to smooth. Let w_i be the population in i, and Δ_{ij} the geodesic distance between locations i, j. Then, the smoothed value is

$$x_i^{smoothed} = \frac{\sum_j w_j x_j e^{-\left(\frac{\Delta_{ij}}{\lambda}\right)^2}}{\sum_j w_j e^{-\left(\frac{\Delta_{ij}}{\lambda}\right)^2}}$$

Where λ is the characteristic distance parameter. The sum runs over all the locations.

Additional results

Mobility reduction (week April 06-12)	**outgoing**		**internal**	
	Pearson	p-value	Pearson	p-value
Number of hospitalized per 100,000 inhabitants (April 05)	0.73	<0.01	0.55	0.053
Standard of living - 9th decile	0.63	0.02	0.72	<0.01
% of active population in age 24-59	0.91	<0.01	0.76	<0.01
% of highly impacted workers	0.80	<0.01	0.64	0.02

Table S1. Correlation coefficients. The table reports the correlation coefficients and their p-value for the four indicators considered and internal and outgoing regional mobility.

Mobility reduction (week April 06-12)	**outgoing**		**internal**	
	Pearson	p-value	Pearson	p-value
Number of hospitalized per 100,000 inhabitants (April 05)	0.57	0.03	0.34	0.14
Standard of living - 9th decile	0.12	0.36	0.61	0.02
% of active population in age 24-59	0.85	<0.01	0.63	0.01
% of highly impacted workers	0.61	0.02	0.42	0.08

Table S2. Correlation coefficients without Île-de-France. The table reports the correlation coefficients and their p-value for the four indicators considered and internal and outgoing regional mobility, computed excluding Île-de-France.

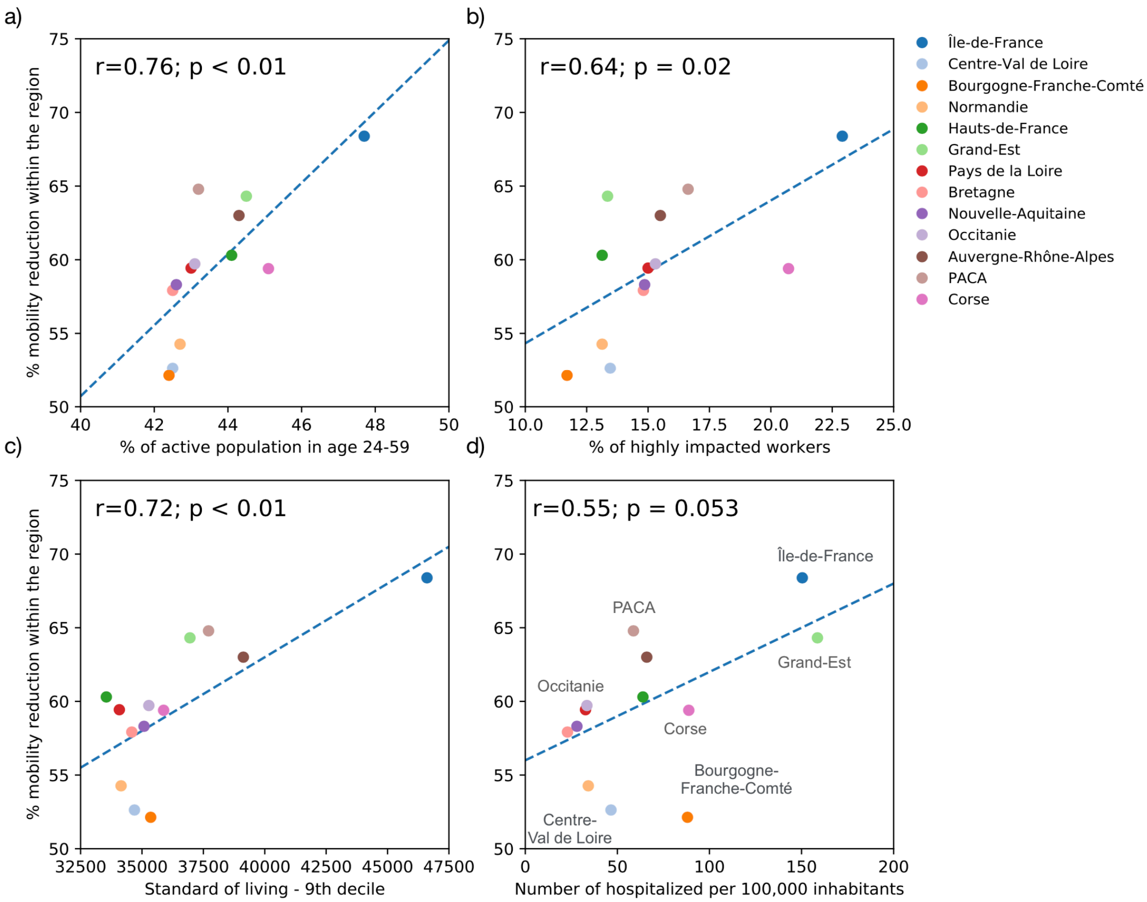

Figure S1. Reduction in internal mobility for the week April 6-12, 2020 vs. epidemic, socio-economic, and demographic indicators. The following plot is the equivalent of Figure 4 for internal mobility. Correlation is evaluated between outgoing traffic and the four considered indicators: a) the population in active age (24-59 years old), b) the fraction of employees in the sectors mostly affected by lockdown. c) the 90th percentile of the regional standard of living. Pearson correlation coefficients and their p-values are reported, d) the cumulated number of COVID-19 hospitalizations per 100,000 inhabitants on April 05, 2020.