Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: a population-based study

Giulia Pullano, Eugenio Valdano*, Nicola Scarpa, Stefania Rubrichi†, Vittoria Colizza†*

Summary

Background On March 17, 2020, French authorities implemented a nationwide lockdown to respond to the COVID-19 epidemic and curb the surge of patients requiring critical care. Assessing the effect of lockdown on individual displacements is essential to quantify achievable mobility reductions and identify the factors driving the changes in social dynamics that affected viral diffusion. We aimed to use mobile phone data to study how mobility in France changed before and during lockdown, breaking down our findings by trip distance, user age and residency, and time of day, and analysing regional data and spatial heterogeneities.

Methods For this population-based study, we used temporally resolved travel flows among 1436 administrative areas of mainland France reconstructed from mobile phone trajectories. Data were stratified by age class (younger than 18 years, 18–64 years, and 65 years or older). We distinguished between residents and non-residents and used population data and regional socioeconomic indicators from the French National Statistical Institute. We measured mobility changes before and during lockdown at both local and country scales using a case-crossover framework. We analysed all trips combined and trips longer than 100 km (termed long trips), and separated trips by daytime or night-time, weekdays or weekends, and rush hours.

Findings Lockdown caused a 65% reduction in the countrywide number of displacements (from about 57 million to about 20 million trips per day) and was particularly effective in reducing work-related short-range mobility, especially during rush hour, and long trips. Geographical heterogeneities showed anomalous increases in long-range movements even before lockdown announcement that were tightly localised in space. During lockdown, mobility drops were unevenly distributed across regions (eg, Île-de-France, the region of Paris, went from 585 000 to 117 000 outgoing trips per day). They were strongly associated with active populations, workers employed in sectors highly affected by lockdown, and number of hospitalisations per region, and moderately associated with the socioeconomic level of the regions. Major cities largely shrank their pattern of connectivity, reducing it mainly to short-range commuting (95% of traffic leaving Paris was contained in a 201 km radius before lockdown, which was reduced to 29 km during lockdown).

Interpretation Lockdown was effective in reducing population mobility across scales. Caution should be taken in the timing of policy announcements and implementation, because anomalous mobility followed policy announcements, which might act as seeding events. Conversely, risk aversion might be beneficial in further decreasing mobility in highly affected regions. We also identified socioeconomic and demographic constraints to the efficacy of restrictions. The unveiled links between geography, demography, and timing of the response to mobility restrictions might help to design interventions that minimise invasiveness while contributing to the current epidemic response.

Funding Agence Nationale de la Recherche, EU, REACTing.

Lancet Digit Health 2020; 2: e638–49

Published Online October 28, 2020 https://doi.org/10.1016/S2589-7500(20)30243-0

*Contributed equally

†Contributed equally

INSERM, Sorbonne Université, Pierre Louis Institute of Epidemiology and Public Health, Paris, France (G Pullano MSc, E Valdano PhD, N Scarpa MSc, V Colizza PhD); **Orange Labs, Sociology and Economics of Networks and Services, Chatillon, France** (G Pullano, S Rubrichi PhD); **and Tokyo Tech World Research Hub Initiative, Institute of Innovative Research, Tokyo Institute of Technology, Tokyo, Japan** (V Colizza)

Correspondence to: Vittoria Colizza, INSERM, Sorbonne Université, Pierre Louis Institute of Epidemiology and Public Health, Paris 75012, France **vittoria.colizza@inserm.fr**

Introduction

COVID-19 is a disease caused by severe acute respiratory syndrome coronavirus 2, which rapidly spread around the world, leading to the currently ongoing pandemic. In early 2020, French authorities responded to the rapid growth of COVID-19 cases by imposing heavy restrictions on mobility, as did 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 health-care system.[2] As these restrictions were gradually being phased out, it was essential to measure changes in human mobility first to quantitatively determine how imposed measures and recommendations (eg, regarding remote working where possible, or banning leisure trips) translated into reduced mobility at specific scales and times; second, to inform models

Research in context

Evidence before this study

We searched PubMed, MedRxiv, BioRxiv, and Arxiv for articles in English published up to May 20, 2020, with the search terms "COVID-19", "human behavior", and "mobility data". Given the rapid evolution of the pandemic, we also monitored news through Google Alerts (languages: English, French; source: News). Our search yielded 324 studies. Mobility during lockdown was analysed in various countries with use of different sources, including mobile phone records. No such study was available for France, except for the news in the press about individuals leaving the Paris area on the day of lockdown enforcement. Two studies associated socioeconomic indicators and mobility reductions. No study considered risk aversion.

Added value of this study

Governments enforced movement restrictions to slow the spread of COVID-19 and relieve the pressure on health-care systems. Our study systematically quantified the effect of restrictions in France, spanning different spatial and temporal scales. We linked heterogeneous drops in mobility across regions to the risk aversion induced by the severity of the epidemic occurring in the regions. More generally, we showed that mobility reductions were a combination of rigid constraints (eg, labour sectors most affected by lockdown), socioeconomic factors, and behavioural response.

Implications of all the available evidence

By untangling the effects of restrictions in terms of behavioural adaptations, individual socioeconomic factors, and labour sectors, our research is key to predicting how and where restrictions will be most effective in reducing population mobility and mixing. This will, in turn, help tune the phase-in and phase-out of present and future movement restrictions.

estimating the effectiveness of the ongoing lockdown in reducing the epidemic spread;[2,3] and third, to identify the driving factors associated with documented reductions to help devise social distancing measures needed for the post-lockdown phase. Accessing human mobility data is now possible at several spatial and time scales and often in nearly real time. These data have been useful in many epidemiological contexts[4]—including, for example, the West Africa Ebola epidemic[5]—and are being used for the COVID-19 pandemic in many countries,[6] namely Belgium,[7] Germany,[8] India,[9] Italy,[10] Poland,[11] Spain,[12] the UK,[13] and the USA.[14,15]

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 analysed over time to study population patterns without any information on individual users, safeguarding privacy.[6] In this study, we used data provided by Flux Vision (Orange Business Services, Paris, France) and studied how mobility in France changed before and during lockdown. We broke down our results by trip distance, user age and residency, and time of day, and we analysed regional data and spatial heterogeneities. We investigated behavioural 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.

See Online for appendix

Methods

Timeline of the COVID-19 epidemic in France

Three phases have marked the French response to the COVID-19 pandemic (figure 1). Phase 1 started on Jan 10, 2020. Its aim was to detect imported cases and identify local transmissions through case-contact investigations. Phase 2 started on Feb 29, 2020, upon appearance of localised clusters and added targeted social distancing interventions around reported clusters (eg, school closures and gatherings and public transport bans). Phase 3 was declared on March 14, 2020, when the virus was recognised to actively circulate in the territory, and quickly required nationwide restrictions culminating in the enforcement of lockdown.

Data source

Mobility data were provided by Flux Vision in the form of displacement matrices. These comprised origin-destination travel flows among 1436 geographical areas of mainland France. For each pair of locations and any given day, data were provided stratified by age class (younger than 18 years, 18–64 years, and 65 years or older). Each area belongs to one of 13 regions, which are the subnational administrative divisions of mainland France. Details on data format and extraction are presented in the appendix (pp 2–3). Mobile phone data were previously anonymised in compliance with strict privacy requirements, presented to and audited by the French data protection authority (Commission Nationale de l'Informatique et des Libertés).

Regional hospitalisation data and COVID-19-related deaths up to April 5 were obtained from Santé Publique France.[16] We used population data and regional socioeconomic indicators from the French National Statistical Institute (INSEE):[17] the proportion of the population in the age range of 24–59 years, which includes most of the working-age population;[17] and the standard of living—ninth decile, defined as the ninth decile of the household's gross disposable income divided by the number of consumption units (which measure household size, one unit for the first adult, 0·5 units for each additional person

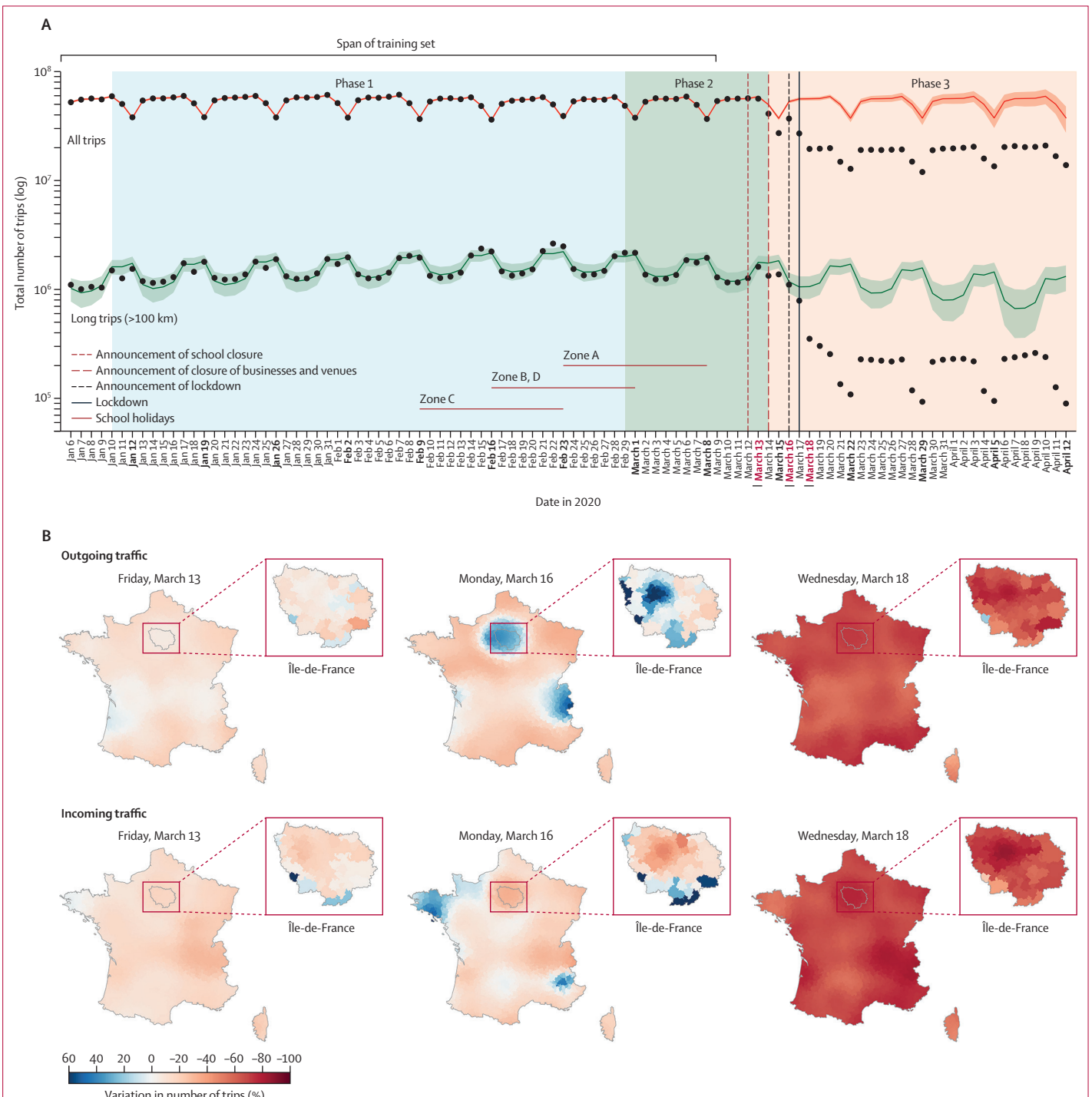

Figure 1: **Phases of the COVID-19 epidemic in France, and its effect on mobility patterns**
(A) Coloured areas correspond to the different phases of the epidemic response, and red lines mark main government interventions; zones A–D are four government-defined geographical areas of France (Paris is in zone C); dashed vertical lines indicate announcements made by French authorities; school closures were to be implemented starting March 16; the announcement of closure of non-essential businesses was done with immediate effect; the announcement of lockdown was done on March 16, to be implemented the day after at noon, and the black solid vertical line on March 17, 2020, indicates the beginning of lockdown; the black dots track the temporal change of the total number of daily trips measured from mobile phone data in France from Jan 6 to April 12; each timeline is fitted with the training set (thin lines) going from Jan 6 to March 9, with extrapolation up to April 12; shaded areas represent 95% credibility intervals. (B) Maps show the variation in incoming and outgoing traffic compared with the unperturbed baseline predicted by the fit; the chosen dates were March 13, March 16 (day before lockdown), and March 18 (day after lockdown enforcement).

aged 14 years or older, and 0·3 for each child younger than 14 years).

Employment data were obtained from INSEE and the French Ministry of Labor.[18] As an indicator, we used the portion of employed workers in the sectors mostly affected by lockdown. These are the sectors in which at least 50% of employees stopped working (eg, hotels, hospitality, food services, and construction) or had been working remotely (eg, finance, insurance, or technology).[18]

Timeline fit and prediction

For **Prophet** see https://facebook.github.io/prophet/.

To fit and forecast the time series, we used the forecasting procedure Prophet (Facebook Open Source, Menlo Park, CA, USA). Prophet decomposes a time series into non-periodic and periodic components, which are then fitted with use of the Markov chain Monte Carlo method (appendix p 4). We fitted Prophet on traffic flow data from Jan 6 to March 9, 2020 (training set of the model), and extrapolated traffic flow after March 9, assuming no perturbation due to COVID-19 or associated interventions. We then measured the deviation of observed traffic from the predicted temporal evolution of unperturbed traffic over time.

Trip analysis and mobility reduction during lockdown

Our analyses were done on all trips and on trips for which geodesic distance between location centroids was longer than 100 km (termed long trips). This cutoff effectively discarded commuting, because approximately 95% of daily work-related trips are shorter than 100 km.[17] We distinguished between residents—users with French SIM cards—and non-residents. We broke down data by the three age classes. We classified trips by their time of day: daytime (0701 h to 1900 h) or night-time (1901 h to 0700 h), and we distinguished between weekdays and weekends. During weekdays, we also considered rush hours (0700 h to 0900 h and 1700 h to 1900 h).

We computed mobility reduction during lockdown in a case-crossover framework by comparing the week starting on April 6, 2020 (3 weeks into lockdown), to the week starting Feb 3 (control week). Feb 3 was chosen because it was before school holidays and after strikes of public transport.

Statistical analysis

All statistical analyses were done in R, version 3.6.1. We did multivariate correlation by standardising the variables and doing a multivariate linear regression. Two-sided significance of Pearson's coefficients was determined at a level of 0·05. The coefficient of variation was defined as the sample SD divided by the sample mean, expressed in percentage points.

Network analysis and maps

For the network analysis, the nodes in the networks represent the geographical locations in which we divided mainland France, and links represent trips between locations. Links were directed (trips have origins and destinations), weighted (by the number of trips linking two locations), and evolved over time. We used standard Python libraries, among which the NetworkX library. Link persistence probability at a given week was defined as the probability that a connection present in the network during Feb 3–9 (control week) was still present in the week under consideration.

To smooth spatial data in the maps, we used a Gaussian kernel (appendix p 4). The radius containing 95% of outgoing traffic from a city was computed by considering all mobility links that started from that city, each with its geodesic distance. The links were included incrementally from the shortest to the longest, until the cumulative sum of the weights of the included links reached 95% of the total outgoing traffic.

Role of the funding source

The funders had no role in study design, data collection, data analysis, data interpretation, writing of the manuscript, and decision to submit. All the authors had full access to all the data used in the study and had final responsibility for the decision to submit for publication.

Results

Although 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 effect on mobility in France (figure 1A). This transition occurred before the announcement (on March 16) and implementation (on March 17) of lockdown measures and saw nationwide mobility go from approximately 60 million trips per day down to approximately 20 million trips after lockdown entered into effect. The shock to mobility spread out over a transition period lasting almost a week.

Starting March 14, 2020, total flow was significantly lower than the predicted unperturbed traffic (outside the 95% credible interval to lower than 41 million), as a probable consequence of the start of phase 3. Mobility further decreased by 34% on Sunday, March 15, when local elections took place. Instead, a 36% rise in traffic occurred on the day before lockdown enforcement. Traffic volume on that day was markedly higher than in the surrounding days, but still lower than the predicted baseline and possibly similar to the typical Sunday-to-Monday pattern. The number of long trips (>100 km) were also significantly—albeit slightly—lower than the predicted baseline during the weekend (March 14–15). However, trips went back to seemingly normal values on March 16, with a volume in agreement with the unperturbed prediction, and nearly normal values on lockdown day. However, this country-level behaviour hid anomalous deviations from the predicted mobility behaviour in specific locations (figure 1B). Spikes in outgoing traffic were distinctively visible in Île-de-France (the region of Paris) and, at the same time, in incoming traffic in Normandy and Brittany. These spikes

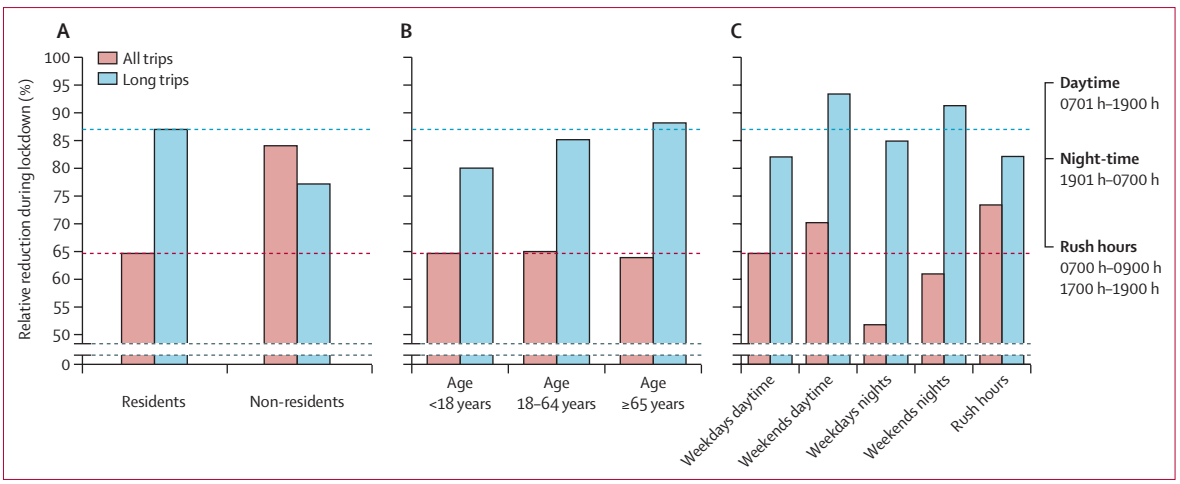

Figure 2: **Mobility reduction during lockdown across user type, age, and time of day**
Reduction was computed as the mean over the week starting Monday, April 6, 2020, with respect to the mean over the first week of February (starting Feb 3). Relative reduction was broken down by residency status (A), age class (B), and time of day (C) and assessed for all trips and for long trips (>100 km). Horizontal dashed lines indicate relative reduction on all residents for all trips and for long trips.

measured the pre-lockdown exodus out of Paris that occurred before lockdown took effect.[19] 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 southeast of France, close to the Alps, as reported previously.[19]

Mobility patterns quickly entered a new equilibrium after lockdown enforcement, marking the end of the transition period. Using a case-crossover framework, we found that lockdown decreased the overall number of trips made by residents by 65% (from 57 million to 20 million trips per day; figure 2A). Reduction was stronger for trips made by non-residents (approximately 85% reduction, from 1·62 million to 0·25 million). However, the number of trips made by non-residents was very small even before lockdown compared with that of French residents (3%); therefore we excluded them from the rest of the analysis. Long-range traffic (>100 km) was disrupted more severely than average disruption of all trips combined (86% reduction, from 1·7 million to 0·24 million trips per day; figure 2A). This was probably associated with a disruption of long-range transportation (eg, trains and flights) and the ban of leisure-related trips, which was also supported by the almost disappearance of long trips during the weekend (figure 2C).

Mobility reduction in the number of total trips was homogeneously distributed across age classes (figure 2B). However, when considering long trips (>100 km) alone, reduction increased with age, with those aged 65 years or older reducing their long trips by 88% (from 250 000 to 30 000 trips per day).

Drops in mobility were uneven across the time of the day (figure 2C). Movements during rush hours were the most disrupted, with the combined effect of school closure and remote working leading to an approximately 75% reduction (from 4·6 million to 1·2 million trips per h) in mobility. Daytime movements during weekends also exhibited a higher than combined average decrease, suggesting a successful reduction of recreational activities. Night-time movements during weekdays recorded the lowest reduction, well below average. This might be due to unavoidable work-related mobility, the effect of which is however likely to be limited because these movements make up only a quarter of the total daily volume of all trips. Long-range mobility almost completely stopped during weekends (94% decrease, from 3 million to 0·17 million trips per day, for daytime and night-time combined).

Traffic reductions were not homogeneous across the 13 regions of mainland France. Reduction of internal traffic was above average in four regions (Île-de-France, Auvergne-Rhône-Alpes, Grand Est, and Provence-Alpes-Côte d'Azur), whereas reductions were markedly below average in Normandy, Bourgogne-Franche-Comté, and Centre-Val de Loire (figure 3). Similar fluctuations were visible in outgoing traffic (coefficient of variation 8·4% compared with 8·0% for internal traffic). Île-de-France, Hauts-de-France, and Grand Est all had above-average reductions in outgoing mobility, as high as 80% (from 585 000 to 117 000 trips per week) for Île-de-France. Corsica also had a reduction similar to that in Île-de-France, showing a clear disruption of the long-range connections linking the island to mainland France. Similar reductions were observed with incoming fluxes in the regions (data not shown).

The effect of nationwide lockdown on the reduction of outgoing mobility per region was strongly associated with the portion of the population in the most active age range (24–59 years;[17] Pearson's r=0·91, p<0·0001) and the portion of workers employed in sectors that substantially modified their organisation during

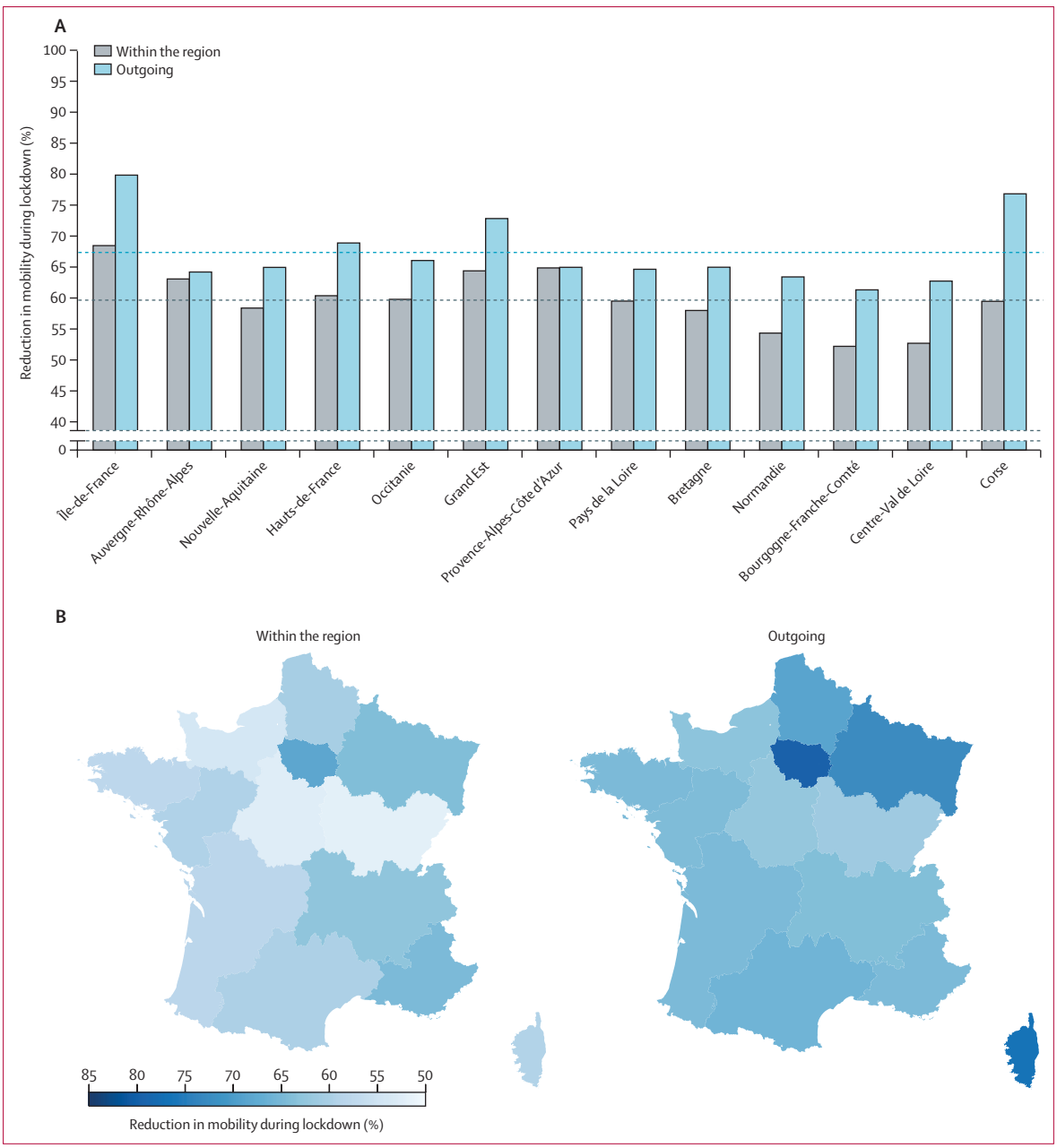

Figure 3: **Lockdown-induced mobility reduction across regions**
(A) Breakdown of mobility reduction by region in mainland France; horizontal lines indicate the corresponding averages across regions, according to type of trip. (B) Map visualisation of the breakdown of mobility reduction.

lockdown due to remote working or partial or full closure of activities (Pearson's r=0·80, p<0·0001; figure 4, appendix p 5). The reduction in mobility was moderately associated with regional economic disparities, in terms of a positive correlation with the ninth decile of the standard of living of the region (Pearson's r=0·63, p=0·020).

Regional drops in mobility in a given week (April 6–12, 2020) were strongly associated with COVID-19 hospitalisation rates registered and communicated in the week before (ending April 5; Pearson's r=0·73, p<0·0001; figure 4). Analogously, these regional drops were strongly correlated to COVID-19-related deaths recorded over the same period as hospitalisations (Pearson's r=0·63, p=0·022). Additionally, COVID-19 hospitalisations and deaths were highly correlated with each other (Pearson's r=0·97, p<0·0001).

Similar results were obtained for drops in mobility within regions, though the association with the hospitalisation rate per region was not significant (appendix pp 5–6). Taking out the datapoint of Île-de-France—the region

mostly affected by a departure of inhabitants for relocation in other regions—led to similar results (appendix p 5). We also did a multivariate analysis that included the behavioural, demographic, and socioeconomic factors considered simultaneously (appendix p 7). Significant associations remained significant after adjustment. The correlation with the ninth decile of the standard of living changed sign (from positive to negative) after adjustment.

When assessing disruption of mobility connections, we found that some connections completely disappeared, as individuals stopped going from one location to another (figure 5). Connection persistence probability (figure 5B) decreased steadily during the transition period, with 67% of connections (397 000 of 596 000) surviving in the week of school closure and non-essential activity closure announcements (March 9–15), and 50% surviving in the week of the announcement and implementation of lockdown (March 16–22). The decrease then stabilised in the first full week of lockdown (with 34% [205 000 of 596 000] of connections surviving, March 23) and beyond. Long connections were less resilient than average, with only 26% (129 000 of 497 000) surviving lockdown.

After lockdown effects stabilised, connections characterised by small traffic before restrictions (weak connections) were the most likely to disappear, with 70% of them (417 000 connections) corresponding to 100 trips per week (figure 5C). However, the traffic lost on these connections barely contributed to total traffic reduction (3% contribution, or 7·2 million weekly trips). Restricting the analysis to long mobility connections, the portion of the weak connections disappearing increased slightly (from 70% to 89%, 442 000 connections), but with a reduction of 47% (5·7 million weekly trips) of traffic.

The disruption in connections occurred with some delay compared with reductions in traffic. For example, on Monday, March 16—the day before lockdown—traffic was reduced by 29% compared with that on the previous Monday (from 51 million to 36 million trips), but the number of connections went down by only 4% (from 219 000 to 210 000). One week later, traffic drop was 65% (18 million trips) and the drop in the number of connections was 57% (94 000).

Restrictions on mobility during lockdown had an uneven effect on the ten most populated French cities (figure 6). 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 mobility (figure 6). But reductions varied, from more than 86% (Paris, from a radius of 201 km to 29 km) to approximately 60% (Strasbourg, from 95 km to 37 km, and Lille, from 78 km to 31 km), mainly due to different patterns of commuting and connectivity characterising the mobility of each city. Connections among main cities also disappeared. During lockdown, we no longer detected mobility from Bordeaux, Montpellier, and Nantes to Lyon, or from Montpellier to Strasbourg (figure 6).

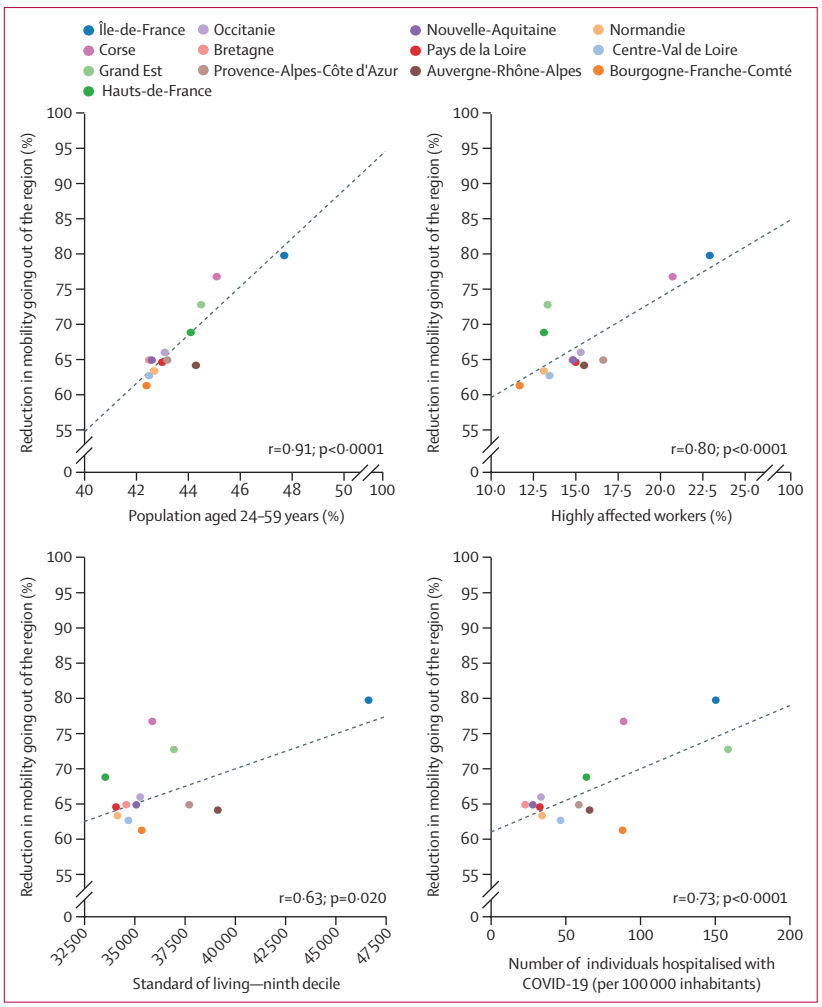

Figure 4: **Reduction in outgoing mobility during April 6–12, 2020, versus demographic, socioeconomic, and epidemic indicators**

Correlation was evaluated between variations in the outgoing traffic and the four considered indicators: population in active age (24–59 years), portion of employees in the sectors mostly affected by lockdown, the ninth decile of the regional standard of living,[17] and the cumulative number of COVID-19 hospitalisations per 100 000 inhabitants on April 5, 2020. Pearson's correlation coefficients and their p values are reported.

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%, similar to reductions found in Belgium,[7] Spain,[12] and Italy[10] during lockdown, albeit different data sources, spatial resolutions, and definitions of mobility proxies prevent direct numerical comparisons.

The transition signalling the drop in mobility lasted almost a week, anticipating the enforcement of lockdown and inducing opposite behaviours in mobility. Individuals started to spontaneously reduce their mobility on March 14 after the announcement of school closures, probably because of fear of the growing epidemic and heightened risk aversion[20,21] generated by the first governmental decision on nationwide interventions. At

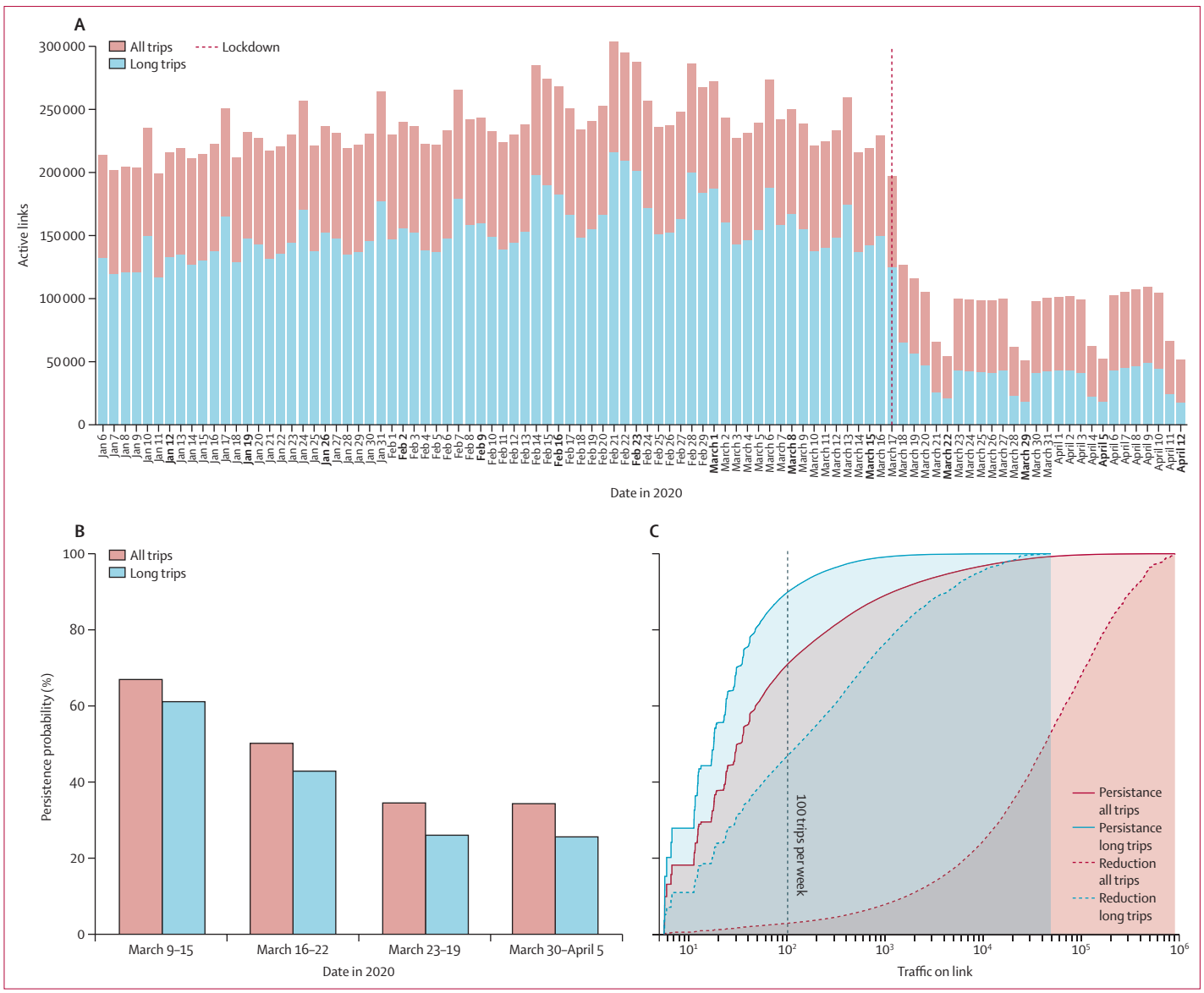

Figure 5: **Network analysis**

(A) Number of mobility connections between French locations over time. (B) Link persistence probability, defined as the probability that a connection present during week Feb 3–9 was still present in one of the four selected weeks: before lockdown (March 9–15), during enforcement (March 16–22), and during lockdown (March 23–29 and March 30 to April 5). (C) Persistence probability and traffic reduction in relation with traffic; for a given value of traffic on link, solid lines measure the portion of broken links that used to have, at most, that weight in the baseline week; dashed lines report the portion of missing traffic that was lost on connections that used to have, at most, a certain weight in the baseline week.

the same time, fear of an imminent change in policy imposing stricter restrictions—as had already been implemented in Italy, Spain, and Austria—pushed individuals to relocate themselves to even farther away regions to spend the period of lockdown, if put in place. The exodus, largely covered by the press,[19] started before the announcement of lockdown and led to anomalous increases in mobility flows out of some regions (eg, Île-de-France) and into others (eg, Normandy). Such behaviour was similarly reported in China (out of Wuhan), in Italy (north to south), and in India.[9] It shows that the timing of when a policy is announced might disrupt social dynamics as much as the direct effect of the policy itself, at least in the short term. Therefore, increased caution should be considered by policy makers in the period from announcements to enforcement to avoid unwanted seeding events (clusters started by an infectious individual coming from a different geographical location) during an epidemic. These events were not observed in the receiving regions because lockdown strongly suppressed epidemic activity countrywide. Notwithstanding, they might become important when phasing out restrictions, as less strict social distancing measures might prevent such suppression.

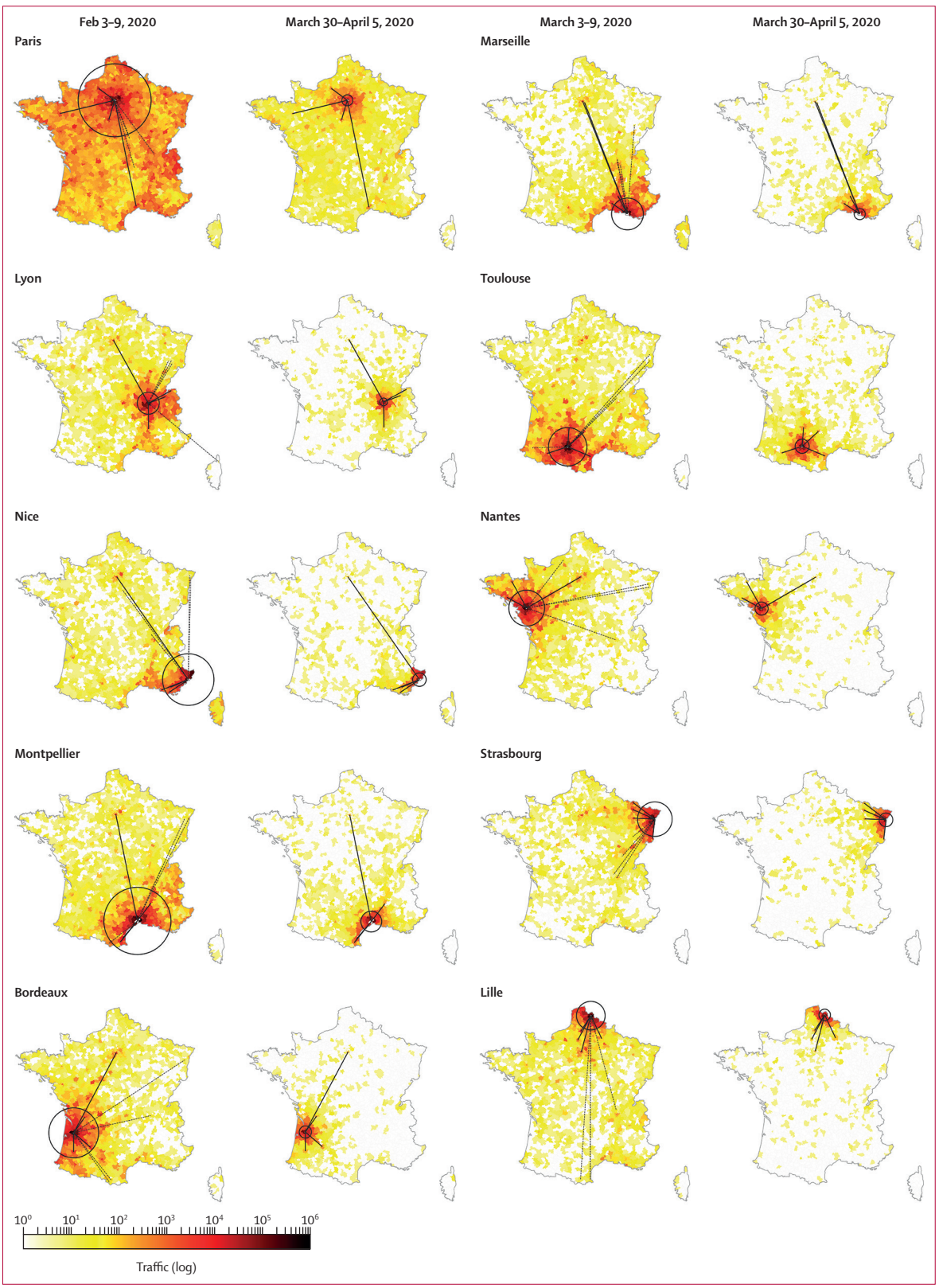

Figure 6: **Outgoing egocentric networks of the ten most populated cities in France during baseline week (starting Feb 3, 2020) and during lockdown week, starting March 30**
Locations are coloured by incoming traffic from the selected city. Solid lines indicate links that persisted during lockdown. Dashed lines are links that disappeared. Both types of locations were selected to be the top ranked by traffic during the baseline week. The circles contain 95% of the outgoing traffic from the respective city.

Region-specific interventions might increase this risk of seeding events by inducing similar behavioural responses. For instance, the state of New York (USA) reported increased mobility in counties with no imposed lockdown.[15] From this perspective, nationwide interventions and restrictions limiting displacements were adopted by several countries 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 for every ten additional hospitalisations per 100 000 inhabitants. A similar association, but with confirmed cases, was observed in Germany.[8] These findings suggest that individuals witnessing a larger COVID-19 burden on the hospital system in their region might have further limited displacements compared with those living in less affected regions. Media has continuously communicated on the epidemic, also providing early on region-specific information on hospitalisations and mounting pressure on the health-care system. Access to this information probably triggered a behavioural response to the perceived risk to reduce exposure, thus increasing compliance to movement restrictions.[21] A similar, though stronger, behaviour was observed during a 3-day national lockdown enforced nationwide in Sierra Leone in March, 2015, in an effort to control the Ebola epidemic.[5] The correlation remained significant even after excluding the region of Île-de-France, which had a reduction in population due to relocation of individuals. Adjusting for the effect of demography and socioeconomic factors did not qualitatively change the associations found, keeping their direction and significance unchanged. We also tested COVID-19-related deaths as a proxy for perceived disease severity and found a similar behaviour, explained by the high correlation between hospitalisations and deaths.

Clearly, other factors might have come into play to differentiate drops in regional mobility. Lockdown restrictions had a severe impact on jobs and the organisation of work. Regions with higher proportions of activity sectors most affected by the lockdown (due to remote working and complete or partial closure of sectors, such as tourism, entertainment, food services, and construction) also had larger drops in mobility. A smaller proportion of active individuals continued to go to work, while the others reduced their displacements. Indeed, regions with larger proportions of the population in the most active age range (24–59 years) were also those where lockdown had the largest effects in mobility. Adjusting for behavioural effects did not change the results.

Uneven mobility drops were also associated with socioeconomic disparities, similarly to findings in Italy.[22] Increasing evidence points to different socioeconomic strata getting uneven shares of the COVID-19 burden.[23] Higher-income jobs can often be done remotely and in confinement, whereas lower-income jobs often 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.[24] Additionally, wealthier population strata can weather short-term financial losses better, making them more prone to stop working and stay at home if they are afraid or sick.[23] Adjusting for disease perception and demography reversed this association of mobility drops and income. This was probably due to complex interactions between behavioural response, demography, and economic development. However, the limited available dataset does not allow for disentangling these effects and inferring causal relationships (appendix pp 5–7).

A strong mobility response to lockdown was documented in the older age class: because older people (aged 65 years or older) are at higher risk of developing severe forms of COVID-19 if infected, they might also have exhibited increased risk aversion. Specifically, they 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 probably boosted the role of mobility restrictions in suppressing viral diffusion, as mounting evidence shows that public transportation is a main risk factor for transmission.[25]

Lockdown caused larger disruptions on long-range mobility compared with those on short-range trips, as also reported in Belgium[7] and Italy.[10] 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 in otherwise unaffected or weakly affected areas.[26] 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.[27] Therefore, long-range mobility restrictions contribute to the geographical containment of the epidemic, especially when epidemic activity shows the patchy geographical pattern observed in many affected countries, including France. Banning trips longer than 100 km thus helps to break the spreading pathways, as observed during the lockdown. Nonetheless, we documented that some long-range connections survived even during lockdown. These movements should be carefully accompanied by strict preventive measures to avoid re-seeding events.

The largest reduction in mobility across distance was reported in Paris. Before lockdown, 95% of outgoing traffic reached destinations within 200 km of the city centre, approximately the distance between Paris and Lille, close to the Belgian border. After lockdown, this radius was reduced to 29 km, the distance from the city centre

to Disneyland Paris. Mobility focused around metropolitan areas, probably serving the needs of individuals in essential professional categories who continued their work-related displacements. A similar geographical fragmentation was observed in Italy.[28]

Our analysis offered plausible interpretations on how the labour market, demographic and socioeconomic indicators, and awareness of increased epidemic risk might have shaped the reduction in mobility, supporting evidence observed in previous[5] and current[24,29] outbreaks. Our findings might extend to other countries in Europe that qualitatively shared France's epidemic wave and interventions.[8–13]

Our study has limitations. Despite the widespread use of mobile phone data to quantify mobility,[4] potential sources of inaccuracy traditionally exist, such as population representativeness, geographical coverage, and heterogeneity in user activity. However, we used passively collected signalling data, which improve temporal accuracy and do not depend on activity behaviour compared with traditional call detail records. The data owner pre-processed the data to be representative of the general population. Large population displacements might also bias regional activity measures. However, the associations we found were robust after removing Île-de-France, the region most affected by the pre-lockdown exodus. Our study is observational, and therefore caution is needed in drawing causal relations between the covariates and changes in mobility. Additionally, the available sample was too small to statistically measure confounding effects rigorously.

One of the goals of mobility restrictions was relieving the strain on the health-care system caused by rapidly increasing hospitalisation rates. The effectiveness of these top-down measures was generally poorly known, and completely unknown for COVID-19. Our study showed that different effects were observed across scales, with larger disruptions on long-range connections leading to a localisation of mobility. By associating the heterogeneous performance of travel restrictions to both a-priori population features (socioeconomic and demographic) and behavioural adaptations to the epidemic and to restrictions themselves, our findings contribute to informing the ongoing epidemic response. Quantitatively characterising how lockdown reshaped mobility might help to design future restrictions that are less pervasive and more targeted.

Contributors

EV, SR, and VC conceived of and designed the study. GP, EV, and NS analysed the data and did the analysis. GP, EV, NS, SR, and VC interpreted the results. EV and VC drafted the Article. All authors contributed to the writing of the final version of the Article.

Declaration of interests

We declare no competing interests.

Data sharing

Mobile phone data are proprietary and confidential. We obtained access to these data from the Orange Business Service Flux Vision within the framework of the research project ANR EVALCOVID-19 (ANR-20-COVI-0007). For legal reasons, the full dataset cannot be published. However, access to the mobility data can be requested from Orange on a contractual basis. Hospitalisation data were obtained from Sanfrom Santé Publique France and are available online.[16] Census and socioeconomic data can be accessed through the official website of the French National Statistical Institute.[17]

Acknowledgments

We thank Luca Ferreri, Sylvain Bourgeois, Erwan Le Quentrec, Zbigniew Smoreda, Chiara Poletto, and Pierre-Yves Boëlle for useful discussions. This study was supported by Agence Nationale de la Recherche projects EVALCOVID-19 (ANR-20-COVI-0007) and DATAREDUX (ANR-19-CE46–0008–03), EU Horizon 2020 grants RECOVER (H2020- 101003589) and MOOD (H2020–874850), and a REACTing COVID-19 modelling grant.

References

1 Anderson RM, Heesterbeek H, Klinkenberg D, Hollingsworth TD. How will country-based mitigation measures influence the course of the COVID-19 epidemic? *Lancet* 2020; **395:** 931–34.

2 Di Domenico L, Pullano G, Sabbatini CE, Boëlle P-Y, Colizza V. Impact of lockdown on COVID-19 epidemic in Île-de-France and possible exit strategies. *BMC Med* 2020; **18:** 240.

3 Di Domenico L, Pullano G, Sabbatini CE, Boëlle P-Y, Colizza V. Expected impact of reopening schools after lockdown on COVID-19 epidemic in Île-de-France. *medRxiv* 2020; published online May 12. https://www.medrxiv.org/content/10.1101/2020.05.08.20095521v1 (preprint).

4 Lai S, Farnham A, Ruktanonchai NW, Tatem AJ. Measuring mobility, disease connectivity and individual risk: a review of using mobile phone data and mHealth for travel medicine. *J Travel Med* 2019; **26:** taz019.

5 Peak CM, Wesolowski A, Zu Erbach-Schoenberg E, et al. Population mobility reductions associated with travel restrictions during the Ebola epidemic in Sierra Leone: use of mobile phone data. *Int J Epidemiol* 2018; **47:** 1562–70.

6 Oliver N, Lepri B, Sterly H, et al. Mobile phone data for informing public health actions across the COVID-19 pandemic life cycle. *Sci Adv* 2020; **6:** eabc0764.

7 Telenet. Covid-19: Belgium analyses telecom data to measure the impact of confinement. 2020. https://press.telenet.be/covid-19-belgium-analyses-telecom-data-to-measure-the-impact-of-confinement# (accessed March 25, 2020).

8 Brockmann D, et al. Covid-19 Mobility Project in Germany. 2020. https://www.covid-19-mobility.org/ (accessed April 20, 2020).

9 Denis E, Telle O, Benkimoun S. Mapping the lockdown effects in India: how geographers can contribute to tackle Covid-19 diffusion. 2020. http://theconversation.com/mapping-the-lockdown-effects-in-india-how-geographers-can-contribute-to-tackle-covid-19-diffusion-136323 (accessed April 20, 2020).

10 Pepe E, Bajardi P, Gauvin L, et al. COVID-19 outbreak response: a first assessment of mobility changes in Italy following national lockdown. *medRxiv* 2020; published online April 7. https://doi.org/10.1101/2020.03.22.20039933.

11 Sas A. Community mobility changes due to the coronavirus (COVID-19) outbreak in Poland. 2020. https://www.statista.com/statistics/1110080/poland-mobility-changes-due-to-covid-19/ (accessed July 7, 2020).

12 Institute for Cross-Disciplinary Physics and Complex Systems. Reducción de la movilidad en España despues de la adopción de las medidas de confinamiento a causa del COVID-19. 2020. https://analytics.ifisc.uib-csic.es/es/respuesta-covid-19/?fbclid=IwAR2C8nA_CWa_AgrD4e_DF5UqWVs-QNZpQeDkxGED-HS1gOyDX5aDpr6UZKY (accessed April 22, 2020).

13 Santana C, Botta F, Barbosa H, Privitera F, Clemente RD. Analysis of human mobility in the UK during the COVID-19 pandemic. 2020. https://doi.org/10.13140/RG.2.2.33207.14240 (accessed April 20, 2020).

14 Bakker M, Berke A, Groh M, Pentland S, Moro E. Effect of social distancing measures in the New York City metropolitan area. 2020. http://curveflattening.media.mit.edu/Social_Distancing_New_York_City.pdf (accessed April 20, 2020).

15 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. *SSRN* 2020; published online April 9. https://doi.org/10.2139/ssrn.3570145 (preprint).

16 Santé Publique France. Indicateurs: cartes, données et graphiques. 2020. https://geodes.santepubliquefrance.fr/#c=indicator&f=0&i=covid_hospit.hosp&s=2020-04-09&t=a01&view=map1 (accessed April 20, 2020).

17 French National Statistical Institute. https://www.insee.fr (accessed April 20, 2020).

18 Direction de l'Animation de la Recherche. Activité et conditions d'emploi de la main-d'œuvre pendant la crise sanitaire Covid-19. 2020. https://dares.travail-emploi.gouv.fr/IMG/pdf/dares_acemo_covid19_synthese_17-04-2020.pdf. (accessed May 15, 2020).

19 Bembaron E. Coronavirus: le grand exode des citadins. 2020. Le Figaro. https://www.lefigaro.fr/secteur/high-tech/le-grand-exode-des-citadins-20200327 (accessed March 25, 2020).

20 Rubin GJ, Amlôt R, Page L, Wessely S. Public perceptions, anxiety, and behaviour change in relation to the swine flu outbreak: cross sectional telephone survey. *BMJ* 2009; **339:** b2651.

21 Funk S, Salathé M, Jansen VAA. Modelling the influence of human behaviour on the spread of infectious diseases: a review. *J R Soc Interface* 2010; **7:** 1247–56.

22 Bonaccorsi G, et al. Economic and social consequences of human mobility restrictions under COVID-19. *Proc Natl Acad Sci USA* 2020; **117:** 15530–35.

23 The Economist. American inequality meets covid-19. 2020. https://www.economist.com/united-states/2020/04/18/american-inequality-meets-covid-19 (accessed April 20, 2020).

24 Morin C, Fourquet J, Le Vern M. Premiers de corvée et premiers de cordée, quel avenir pour le travail déconfiné? 2020. https://jean-jaures.org/nos-productions/premiers-de-corvee-et-premiers-de-cordee-quel-avenir-pour-le-travail-deconfine (accessed April 20, 2020).

25 Bi Q, Wu Y, Mei S, 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* 2020; **20:** 911–19.

26 Balcan D, Colizza V, Gonçalves B, Hu H, Ramasco JJ, Vespignani A. Multiscale mobility networks and the spatial spreading of infectious diseases. *Proc Natl Acad Sci USA* 2009; **106:** 21484–89.

27 Jia JS, Lu X, Yuan Y, Xu G, Jia J, Christakis NA. Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature* 2020; **582:** 389–94.

28 Bonato P, Cintia P, Fabbri F, et al. Mobile phone data analytics against the COVID-19 epidemics in Italy: flow diversity and local job markets during the national lockdown. *arXiv* 2020; published online April 23. https://arxiv.org/abs/2004.11278 (preprint).

29 Valentino-DeVries J, Lu D, Dance GJX. Location data says it all: staying at home during coronavirus is a luxury. The New York Times. 2020. https://www.nytimes.com/interactive/2020/04/03/us/coronavirus-stay-home-rich-poor.html (accessed April 20, 2020).