Presence and mobility of the population during the first wave of Covid-19 outbreak and lockdown in Italy

Paolo Beria, Vardhman Lunkar *

Dipartimento di Architettura e Studi Urbani, Politecnico di Milano, Italy

A B S T R A C T

The non-medical policies implemented by many countries to "flatten the curve" during the COVID-19 outbreak has people stranded in their homes and some, out of their homes unable to return due to the disruptions in the mobility network. The availability of rich datasets (in our case, Facebook) has made it possible to study the mobility dynamics and spatial distribution of people during lockdown in Italy.

Our interpretation is an effort to look deeper, describing the movements occurred during lockdown, including the territorial differences. We observe that, initially, tourists left the country and later Italians abroad managed to return, thereby, stabilising the population. With regards to internal mobility, the earliest affected regions see higher number of stationary users in the initial days of the outbreak while this is less significant for the central/southern regions until the decree for the official lockdown on the 9th of March 2020, due 2 days later. Just before lockdown, there was not a significant exodus of people from the North to the rest of the country, instead, relocation of people between cities and their urban belts, but not towards remote areas. This will be elaborated in conclusions shedding light on possible changes in future cities.

1. Introduction

The outbreak of COVID-19 has resulted in a health crisis on an unprecedented global scale. It has induced stress on the national health systems and has consequently led to extreme measures from the respective governments to contain the virus. The "lockdown" measures adopted to mitigate the spreading of the virus in Italy – for the first time ever at this scale, sadly followed soon by many other countries – has frozen almost every social and economic aspect of the nation. Thus, it is of paramount importance to estimate how the patterns of mobility have been altered during the emergency, as a part of the strategy to mitigate sanitary and economic impacts (Rahman et al., 2020). During crisis situations data from social networks prove to be a valuable source of information for authorities and researchers.

This paper is an application of the *Facebook disaster prevention maps* (a part of the *Facebook – Data for Good* programme), which is a collection of method for processing Facebook data into dynamic spatial-temporal datasets that illustrates how populations are preparing for, impacted by, and coping with a crisis situation. During COVID pandemic, these data have been produced at a national scale for most of the world countries, providing a unique occasion to analyse and interpret the

world mobility changes. The maps utilise anonymized and aggregated data, with focus on current and historic location sensing, information on cell connectivity accompanied with privacy and security maintenance. They are shared with humanitarian organisations and researchers in the days and weeks following a crisis by adding random noise and filtering out small values. Comparing the public response to the interventions in terms of the rate of mobility on a spatial-temporal scale, measured relative to the baseline (pre-crisis conditions), can unarguably provide an insight into the effectiveness of emergency interventions. Consequently, it will help attain better efficiency in case of a resurgence of emergency situations. Thus, an effort is being made to analyse this aggregated data and deduce the presence and movements of people during this period.

The paper starts, in Section 2, with the literature dealing with mobility disruptions during crisis situations. Section 3 gives a brief description of the datasets by defining the metrics used in the analysis. Section 4 addresses the various caveats in the datasets and consequently verifies its degree of representativeness by comparing it with official statistics. The movements datasets have been correlated with a traditional national-scale origin destination matrix (obtained from the transport model i-Tram) and the particularities have been discussed.

Section 5 introduces the COVID-19 outbreak in Italy and the timeline of the salient events that took place afterwards.

The three principal research questions have been addressed in the remainder of the paper. The first one (Section 6) is how much and to what extent people "stayed at home" before, during and at the opening of the lockdown. Despite the media narration of people ignoring the lockdown, data clearly shows that since March (the lockdown was declared on March 11th) the share of people moving and the range of movement fell dramatically to a nearly physiological level (supplies, health workers, necessary trips).

Secondly (Section 7) is if there was an "exodus" of population during the weekend between the announcement of the national lockdown and its commencement. In particular, if a significant movement of people can be observed between the North and the rest of the Country.

Thirdly (Section 8) is about the relocation of people's residence during lockdown. In particular we are interested to verify if cities have emptied and where the population has moved: far away, in the periphery, towards second houses at the sea or countryside or abroad (tourists or expats/migrants and the corresponding return of Italians from abroad). The conclusions, including a discussion about the mobility of future cities, are presented in Section 9.

2. Studying real time mobility during crisis – A Literature review

The COVD outbreak's size and impact has stimulated a huge scientific production from almost every field of research (for a review see Rahmani & Mirmahaleh, 2020). In this section we focus on studies dealing with mobility during crises, and in particular in the use of big-data and/or real time data.

Societal instability and abrupt large-scale population displacement are a common reaction to disease outbreaks or in the case of natural disasters, even a response strategy. These movements have a limited understanding and are tedious to measure but strongly impact societal health. Human Computation methods involving the use of real time social media data have been put into practice and used to support humanitarian efforts for disaster affected communities. Meier (2013) performed an elaborate examination of the available case studies describing specific crowdsourcing methodologies applied to support disaster relief, with special attention to challenges, benefits and outcomes. Real time monitoring of human mobility is of great interest to both researchers and policy makers. The crowdsourced geolocation data can and have proved in the past to serve as proxies of population distribution to answer a standard and basic question, nevertheless of great importance for a crisis response: "Where are the people?". Researchers have been interested in looking at human mobility and social interaction patterns using geotagged social media data. In the context of disasters, Wang & Taylor, 2016 disclosed spatiotemporal patterns of human mobility in different disasters by leveraging geotagged tweets. They inferred that there is a disruption/alteration of the movement of people during disaster events and this disturbance depends on the location of the disaster and its characteristics. Chae et al., 2014 offered a tool to visually represent spatial patterns of twitter user distribution before, during and after Hurricane Sandy and the 2013 Moore (Oklahoma) tornado. Bharti, Lu, Bengtsson, Wetter, and Tatem (2015) correlated and justified two remote and complementary measures, night-time lights satellite imagery and anonymized mobile phone call detail records, to assess average population concentrations as well as dynamic population changes surrounding the humanitarian crisis caused by the internal political conflict in Cote d'Ivoire. Clearly, mobile phone data can provide rich information about some aspects of mobility and disease-spread, such as changes in population location, size of geographical relations, but not about others, such as the change in individual behaviours or transmission chains (Grantz et al., 2020).

In the nearly two years since Disaster Maps were launched by Facebook, the datasets have been used during major disasters in nearly every region of the world. During the Thomas, Carr, Mendocino Complex, and Camp wildfires in the USA, the non-profit organisation Direct Relief used the maps to monitor how populations affected were moving and then used this to guide distribution of hundreds of thousands of respiratory masks, as well as to coordinate with networks of health centres to alert hospitals that might see increased volumes (Snibbe, 2018). In August of 2018, Kerala, India experienced severe flooding that displaced over a million people. SEEDS India used the Facebook Population and Displacement maps to appropriately time and calibrate their works on relief, recovery, and rehabilitation operations. After identifying when people appeared to begin to return home, SEEDS (Sustainable Environment and Ecological Development Society) launched a nationwide collection drive for widely needed items (Gupta, 2018). The Facebook population change maps were used to understand the patterns of displaced population and identified hot and cold spots of population change during the California fires (Jia S., Kim S.H., Nghiem S.V., Doherty P., Kafatos M.C., 2020). During these two mega-fires in California, (Facebook Disaster Maps) FBDM data effectively captured the temporal change of population arising from the placing and lifting of evacuation orders. Coupled with monotonic trends, the fall and rise of cold and hot spots of population revealed the areas with the greatest population drop and potential places to house the displaced residents. During volcanic eruptions in Guatemala and when a combined earthquake and tsunami struck the island of Sulawesi in Indonesia, UNICEF used the Network Coverage maps (part of the Facebook disaster map package) to determine how many people could be reached through U-Report, an outreach tool built on Facebook Messenger. In Guatemala, UNICEF reached 3000 new people providing them with information about what to do after the eruption and in Indonesia, U-report reached 3500 people within 48 h to understand how they were impacted (Brecha Cero, 2018). When Hurricane Maria struck the island of Puerto Rico, Net Hope and the American Red Cross used these maps for the deployment of nearly 100 Wi-Fi services across the island to the areas that were in urgent need of them (Brinkhurst & Crowley, 2018).

More recently, during COVID-19 outbreak, the use of Facebook data and comparable datasets (from mobile phones, apps, etc.) has reached a broader extent, with scholars and institutions working nearly real-time on numerous aspects of the outbreak and of the lockdown. In their ongoing research combined the *Movement data* from Facebook and the economic data from official statistical database to understand the economic downturn of mobility restriction arising from the lockdown in Italy, the first European country affected (Bonaccorsi et al., 2020). In another research work, it was demonstrated that the impact of the lockdown depends on the country's internal mobility structure (Galeazzi et al., 2020). They compared Italy, France and UK and found that the mobility network after the lockdown was more concentrated for UK and France and distributed for Italy. In exploring how variation in mobility relate to some fundamental economic variables, it was found that reduction in connectivity tends to be stronger for high-income inequality municipalities. The first quantitative assessment of the impact of measures on the mobility and the spatial proximity of Italians, was done through the aggregated data provided by Cuebiq (Pepe et al., 2020). They estimated a reduction of 50 % of the total trips between Italian provinces, following the lockdown. In the same week, the average users' radius of gyration had declined by about 50 % and the average degree of the users' proximity network had dropped by 47 % at national level. A combined analysis of human mobility and epidemics in Italy was performed by using raw data (Call detail Records – CDR's and Extended detail Records – XDR'S) provided by the mobile operator WINDTRE (Cintia et al., 2020). They highlighted a striking relation between the negative variation of movement fluxes and the net reproduction number of the virus. They discovered that the reproduction number continues to slowly decrease during lockdown and during the phase 2 (lockdown exit), when the mobility begins to rise again, the reproduction number does not jump to an uncontrolled growth. This, they stated could be because of the non-pharmaceutical interventions (social distancing and usage of personal protective equipment).

Out of Italy, Brennan Klein et al., 2020 studied the changes in mobility of United States through different proxy signals using the mobility data also provided by Cubeiq. They quantified the reduction in mobility at the macro, meso- and microscopic level to examine the degree of social distancing and to answer questions on the trajectory of the pandemic. Kissler et al. (2020) used the aggregated movements map and associated reductions in mobility in and out of the New York boroughs with the prevalence of the SARS-CoV-2 infection. Denis, Telle, Benkimoun, Mukhopadhyay, & Nath (2020) have used the Facebook Movement data to clearly show that lockdown was effective in reducing overall mobility in India and to further realise that cities lost between 4 % and 11 % of their population, while rural population increased by 7 %. In addition to this, some long-distance mobility was observed during the first week of the implementation of the lockdown. Facebook mobility and movement range data were used to understand the impact of the social distancing policy measures on the spread of the SARS-CoV-2 virus in the greater Seattle Area (Burstein et al., 2020). In a follow-up report (Thakkar, Burstein, Hu, Selvaraj, & Klein, 2020), they modelled diagnosis data, permitting them to understand how mobility decreases can be connected to decreases in COVID-19 transmission using reproduction number as a metric. In a similar context to Italy, but focusing on a single city's mobility changes, Aloi et al. (2020) model in detail the lockdown effect in Santander (SP) and provide figures on all modes and purposes. Orro, Novales, Monteagudo, Pérez-López, and Bugarín (2020) look at bus services in A Coruña. Among others, Hashim, Al-Naseri, Al-Maliki, and Al-Ansari (2020), Ropkins and Tate (2020) and Vultaggio, Varrica, and Alaimo (2020), quantify the positive impact of lockdown on air quality. Table 1 provides a systematic summary of literature about quantitative and qualitative national mobility effects observed across the world.

Lockdown impacted differently cities according to their structure and social mix. In Canada (Chan, 2020) Facebook data showed that the reduction of mobility was correlated with population density and share of apartment dwellings, suggesting that the impact is different across census groups. A similar dependence of lockdown response from socioeconomic conditions has been found in Bogotà, where Dueñas, Campi, and Olmos (2020) observed that lower income groups modified less their mobility with respect to higher income groups and in South Africa (Carlitz & Makhura, 2020). Huynh (2020) discussed, through Google Community Mobility reports, the differences in the use of city places according to outbreak evolution, but also to country's cultural factors. In the UK, the ONS (2020) found a clear pattern of population density decrease in London and rest of the country, and an increase of coastal towns (either small or large) during July and August. While this is quite foreseeable, it is interesting that the trend continued also in September, suggesting that the location of inhabitants changed due to outbreak. Interestingly, not all people is affected in the same way by lockdowns. de Haas, Faber, and Hamersma (2020), through a survey, show the change in mobility behaviour of different categories, foreseeing that some changes could become structural, for example in terms of more smart working.

The impact of human mobility and travel restrictions on the potential spread of COVID-19 in Taiwan was modelled (Chang et al., 2020). They compared the impact of intra-city vs. intercity travel restrictions on both the total number of infections and the speed of outbreak spread and developed an interactive application that allows users to vary inputs and assumptions. They found that intra-city travel reductions have a higher impact on overall infection numbers than intercity travel reductions, while intercity travel reductions can narrow the scope of the outbreak and help target resources. In a very elaborate study, researchers were able to use mobile phone data to demonstrate that the distribution of population outflow accurately predicts the relative frequency and geographical distributions of infections (Jia J.S., Lu X., Xu G., Jia J. and Christakis N.A., 2020). Using population flow data, they developed a risk model to track and identify high risk locales of COVID-19 at an early stage, which serves as a valuable tool kit for public health experts and

Table 1

A systematic summary of the relevant literature.

Source	Country	Quantitative findings	Qualitative findings
Orro et al. (2020)	Spain	The minimum percentage of mobility during lockdown was: driving (10.93 %); transit (7.04%); walking (5.82%)	–
Klein et al. (2020)	USA	Mobility reduction: 40–60 %	
Denis et al. (2020)	India	Mobility reduction: 30–90 %	Cities lose population while rural areas gain
Bonaccorsi et al. (2020)	Italy	–	Enhanced economic disparities; mobility contraction is stronger in municipalities where inequality is higher and income per capita is lower.
Galeazzi et al. (2020)	Italy, France, UK	Node reduction: 16 %, 80 %, 21 % respectively; Network efficiency reduction: 65 %, 80 %, 50 % respectively	UK has higher network resilience than Italy while France has the lowest.
de Haas et al. (2020)	The Netherlands	80 % reduction in outdoor activities, 44 % working remotely. The number of trips and distance travelled dropped by 55 % and 68 % respectively	Increased cycle trips, more remote meetings, lesser distances travelled.
Korean Transport Institute	South Korea	30–69 % reduction in mobility	–
Saha, Barman, and Chouhan (2020)	India	Retail and recreation, grocery and pharmacy, visits to parks, transit stations, and workplaces mobility dropped by 73.4 %, 51.2 %, 46.3 %, 66 % and 56.7 % respectively.	Visits to residential places mobility increased as people mostly stayed home.
DGT, 2020	Spain	Interurban traffic decreased by 72 % (weekdays: −65%; weekends: −86%).	Drastic reduction of road accidents
Wielechowski, Czech, and Grzęda (2020)	Poland	77 % drop in public transport passengers.	
Dueñas et al. (2020)	Colombia	Mobility reached a minimum of 16 % two weeks after the lockdown	Higher socioeconomic strata are consistently associated with higher reductions in mobility. Instead, higher shares of informal workers and a measure of multidimensional poverty are linked to lower decreases in mobility.
Pullano et al. (2020)	France	Overall number of trips: -65 %; Foreigners: - ~85 %.	They suggested that the enforcement of lockdown disrupted tourism and impacted more the mobility of foreign nationals in the country

Table 1 (*continued*)

Source	Country	Quantitative findings	Qualitative findings
Born, Dietrich, and Müller (2020)	Sweden	Maximum Reduction in transit and work of 45 % and 50 % but maximum increase in residential and parks by 15 % and 100 %	–
Patel et al. (2020)	New Zealand	8-17 % decrease in PM2.5; 7–20 % decrease in PM10	–
Seo et al. (2020)	South Korea	10 % reduction in PM2.5 and 25 % reduction in PM10	–

policy makers.

This research is an addition to the list, providing a better understanding of local and intercity mobility patterns during the outbreak in one of the earliest hit countries. It is also a step towards validating that *Facebook disaster maps*, coupled with other tools, can be an effective way of comprehending crisis ground realities and could be of potential help to decision-makers in managing them.

3. The datasets

The programme *Facebook Data for Good* made available numerous datasets, also called *Facebook Disaster Maps*, for entire countries and/or for single regions/cities (described in Maas et al., 2019). In the case of Italy, the data is available at the country-scale ("Italy Coronavirus Disease Prevention Map package"), with some more detailed focuses on single cities. For this paper we focus on country-scale data. We will use three of the available datasets:

a the Movement Range.
b the Movement between administrative regions – NUTS-3 (the provinces, in Italy).
c the Facebook Population (Tile Level).

All datasets used contain spatial and temporal information based on the behaviour of Facebook users with active GPS and active Location History. The data is detected passively and is fully anonymised. Individual information is aggregated spatially (either using tiles or administrative borders) and temporally (every eight hours: 00:00AM, 8:00AM and 4:00 PM, corresponding in Italy to 02:00 AM ± 4 h, 10:00 AM ± 4 h, 06:00 PM ± 4 h and perfectly fitting with night, morning and afternoon).

3.1. Movement range

Movement Range trends datasets include two types of metrics.

a Travel Range: explains the average number of level 16 Bing tiles (0.6 km x 0.6 km) that a Facebook user (with location services on) was present during a 24 -h period relative to the pre-crisis levels. Thus, it can be used to measure the degree of change of mobility range.
b Staying Put map: explains the percentage of Facebook users (with location services on) that stay on one of such tile at 3 different hours of the day. Thus, a stationary user is analogous to staying put or staying home.

3.2. Movement between administrative regions

The *Movement between administrative regions* aggregates dynamic movements of users in terms of geographical coordinates. It takes into account who moved from a given cell to another between the time periods. The data is then aggregated at Italian provincial level (corresponding to NUTS-3). The metrics that are provided include:

a Baseline: This indicates the total number of users moving from origin to destination, calculated as an average over the 7–45 days prior to the beginning of the crisis. Since the dataset starts on Feb 24th 2020, Christmas holidays are excluded.
b Crisis: This indicates the total number of users moving from origin to destination during the specified time-period.
c Difference: This indicates the difference (in percentage) between the number of people moving from origin to destination during crisis with respect to the baseline.
d Standard (Z) Score: The number of deviations by which the count of people moving during the crisis differs from the number of people moving anytime during the baseline.

It is important to notice that the entry is present in the dataset only if this value is greater than the threshold (10 movements in an 8 h period), otherwise it is discarded. This introduces an underestimation of flows especially between sparse or very far destinations.

3.3. Facebook population (tiles)

The *Facebook population (tile level)* provides the number of active Facebook users spatialised in a tile matrix. We use the national scale dataset, where the tile size is approx. 4800 m of edge and aggregate basic tiles. The data provided is the number of geo-localized Facebook users every 8 h present in the tile during the crisis and in the corresponding day/hour of the baseline.

The metrics provided include:

a Baseline: This indicates the average number of Facebook users present in the location during the last 90 days prior to the event (in this case 24th of February 2020). The baseline value is segmented by the day of the week and the time window for the metric, to be comparable.
b Crisis: This indicates the average number of Facebook users present in the location during the crisis.
c Difference - The difference between the population at the time of the crisis and the population during the baseline.

4. Representativeness of the dataset

The datasets have the potential to replicate a picture of crisis situations with a certain level of detail and global coverage. However, such type of Location based Social Network data has its limitations and caveats (Grantz et al., 2020). The Facebook users are not fully representative of all demographic and socio-economic groups within a population, as well as their territorial distribution.

In addition, the baseline information refers to 45 (movement) or 90 (presence) days prior to the event and the period could not be a "real" baseline when describing long events. For example, the outbreak started during Winter but deployed during Spring; consequently, any crisis vs. baseline comparison is biased also of the seasonal change. In the movement datasets, any Origin-Destination pair with less than 10 trips has been excluded from the dataset to add noise for privacy reasons. So, a missing O-D pair does not necessarily indicate absence of movement. Thus, it is important to mention that for comparison purposes, only those O-D's are compared which are present in both datasets.

For the above reasons, it is imperative that we understand the degree of representativeness of the datasets before elaborating and interpreting them.

Comparing the baseline population of 24th February and 28th April with the official resident population (ISTAT[1]) – Aggregated analysis

Following the explanation given in the introduction of this section

that the baseline of the population datasets refers to the average of the 90 days before the crisis began and thus could be biased considering that the period includes Christmas, New Year and obviously the winter season, it is important to get an insight into the adherence of the datasets with census data. Consequently, an effort is made to calculate the population penetration of Facebook users relative to the official socio-demographic data provided by ISTAT (National Institute of Statistics) as of 1st January 2019. We have chosen two dates for this comparison: the baseline (before 24th February) and the night of 27th–28th April 2020 when most of Italians abroad returned and most likely occupied their place of origin.[1] Cities are locked and it is more likely to draw a frozen picture of the Italians' official residences.

Since the Facebook-Data for Good program provides aggregate information, the precise segregation of the population according to sex, age and provinces are not available for our dataset. It would therefore be plausible to use Facebook Audience Insights (a new tool designed to help marketers learn more about their target audiences) to understand the general composition of Facebook users. This portal provides a series of statistics, including aggregate information about geography, demographics, purchase behaviour and more. In the population pyramid diagram shown below in Fig. 1, the overage population distribution of Facebook users is compared with the ISTAT[2] data. The proportion of male and female stands coherent for both data sources at approximately 50 % each. The population from 18 to 54 ha s a higher contribution when compared with the official statistics while the population ranging from 54 and above are relatively underrepresented, as expected. Due to usage habits, the elders are typically underrepresented in such data. To the contrary, part of the users could be underage children declaring higher age (Chou, Liu, & Chou, 2019). However, the use of Facebook among the youngest is very limited and the least growing (Kassa, Cuevas, & Cuevas, 2018; Ribeiro, Benevenuto, & Zagheni, 2020). Therefore we can assume that the presence of children below the minimum age of 13 should not bias results more than what happens in other classes.

Spatially, population penetration is homogeneous for both dates since most of the provinces fall within the same range, as represented graphically in Fig. 2. Not far from our expectations, metropolitan provinces like Milan, Bologna, Florence, Rome and Naples show the greater penetration of Facebook (around 7 %), while a few of underpopulated provinces in the South have a lower penetration relative to the national average.

Comparing the baseline population of 24th February with the official resident population (ISTAT) – Disaggregated analysis on age groups

Moving further, we transit our focus from the general population distribution to a more geographically disaggregate measure of
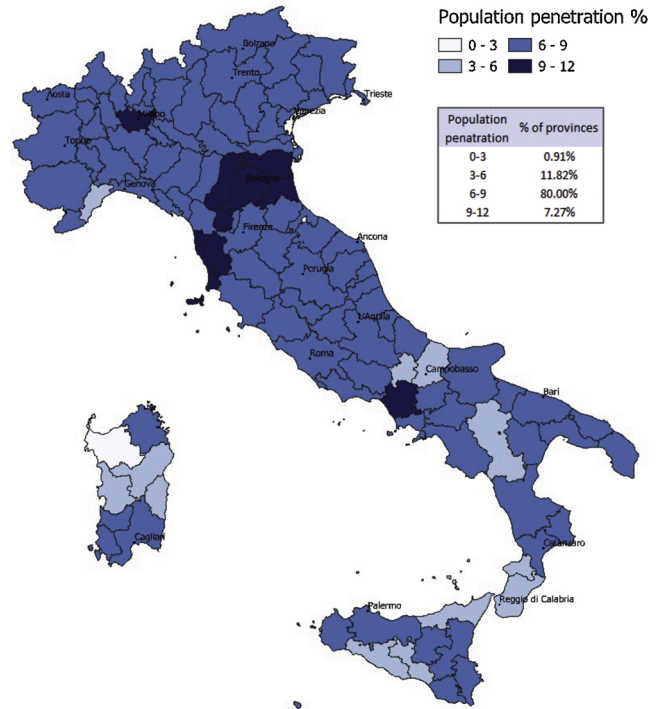

Fig. 1. Comparison of Socio-demographic data of Facebook users and census (ISTAT).

Fig. 2. Population penetration of Facebook Users – 28th April (Aggregated for entire population).

penetration across age groups (Fig. 3). It suggests that the Facebook penetration of the most mobile population (18–54) is the highest and ranges between 6 %–12 % with a very homogenous picture painted for 25–34 and 45–54 with more than 90 % of the provinces falling under the penetration range 9 %–12 %. Just for age groups > 54, a relatively lower and homogeneous range of population penetration is observed (0 %–6 %), with the exception of a main metropolitan areas of Centre and North-West (>6 %).

Overall, we can expect an overestimation of the most mobile groups, but this should not be spatially biasing as classes are reasonably homogeneous across provinces.

4.1. Socio-demographic data (Facebook Audience Insights) with ISTAT – gender

Similarly, transitioning from the national gender representation to a regional scale, there is a strong homogeneity observed across the different regions ranging from 4.28 % for Molise in the South to 6.28 % for Val d'Aosta in the North West. The male and female population penetration are at par for the respective regions and provinces. These penetration rates are a result of aggregation of the penetration rates on a provincial scale. The regions in the Centre and North-West show a greater than average penetration rate (Lombardy, Piemonte, Lazio, Umbria) while the Islands (Sicily and Sardinia) and regions in the South (Molise, Calabria, Basilicata) show lesser than average penetration rates. Since the regional penetration is a result of the aggregation of provincial data, Table 2 of Appendix B (in Supplementary material) enlists the Top 10 provinces that have superseded others in terms of population penetration rates. Metropolitan cities have a higher penetration rate while smaller provinces tend to have lesser penetration rates by gender.

4.2. Facebook Movement Matrix with the I-TRAM model

The representativeness of the Facebook Movement matrix also requires to be checked. Spelta, Flori, Pierri, Bonaccorsi, and Pammolli (2020) checked (and found) correlation with official ISTAT matrix.
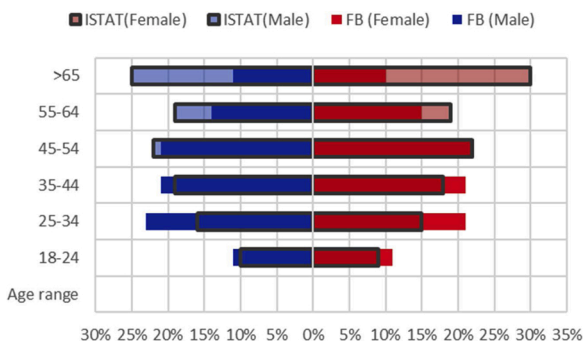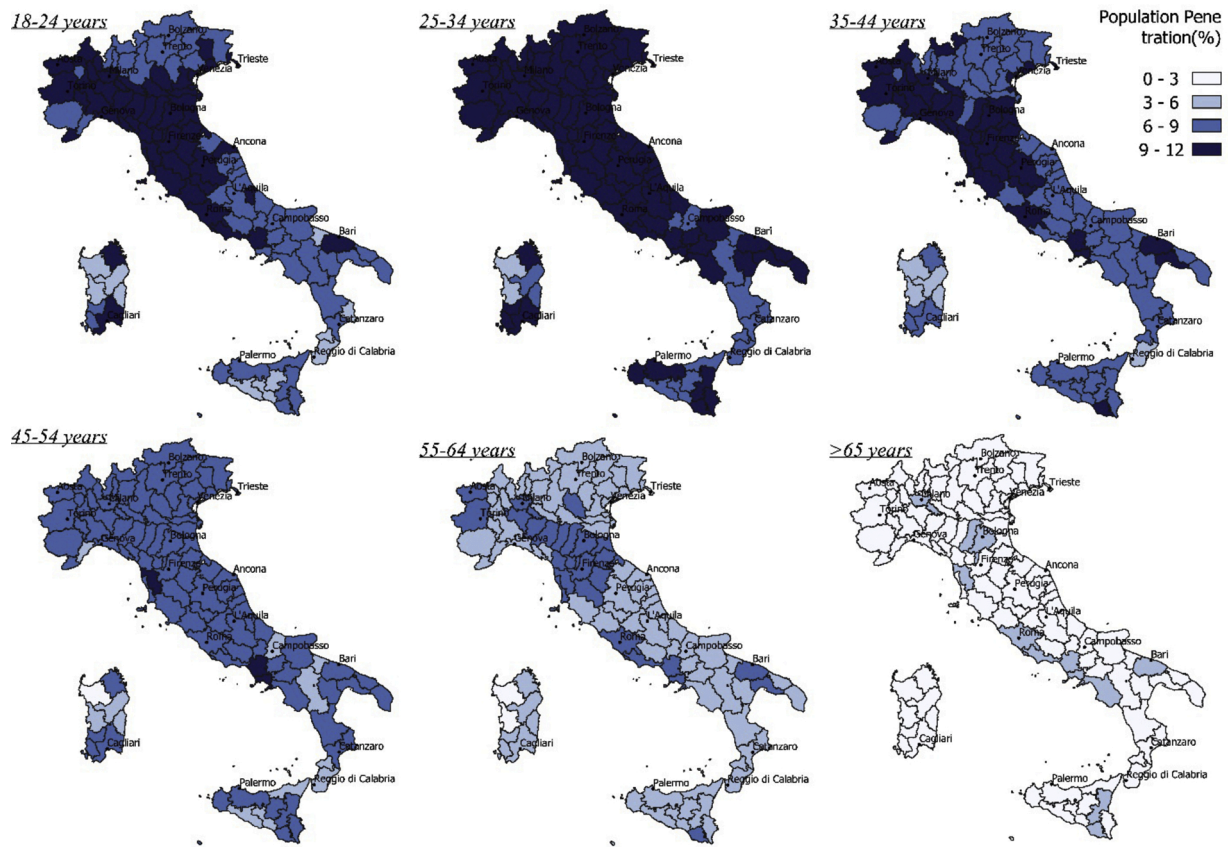
Fig. 3. Population penetration of Facebook users (Disaggregated age groups).

However, such matrix is old (2011) and includes only commuters. For this reason, we checked the correlation with a more recent matrix including also non-systematic trips – that are dominant at the national scale. The O-D Matrix of the i-TRAM[3] model has the required characteristics. The metric correlated here is the average daily flow (excluding weekends) and the check is separate for the movements between administrative regions and the internal movements. A simple linear regression is performed to correlate these metrics and as shown in the Fig. 4, we observe a fairly strong matching with the reference matrix. It is worthwhile to mention that only those O-D's are considered that are common to both the matrices, i.e. excluding those absent in Facebook matrix because with less than 10 trips. The aggregated Facebook Regional Matrix has been published in Table 1 of Appendix A (in Supplementary material).

5. The COVID-19 outbreak in Italy

Italy was the first European and Western country where the 2020 COVID-19 outbreak developed locally. The first confirmed cases were separately found in Codogno area (south of Milan) and in Veneto near Padua, both on February 21st. Two cases were already found in Rome on January 31st, but they were Chinese tourists that contracted the virus in China and were promptly isolated. Other cases probably spread in Europe even before the Italian ones, but they were not recognised or were isolated.

On February 22nd Italian government established a local lockdown in 11 municipalities (10 in Lombardy and one in Veneto). On March 4th all schools and universities in the country were closed. In Northern Italy mobility already dropped since the 24th of February, with companies

opting to remote- or smart-working and people avoiding public transport.

The country-scale lockdown, the first in Europe, started on March 11th: all working places, except essential ones, were closed and people was requested to stay home except for food purchasing. The possibility of a large-scale lockdown was anticipated on March 7th, when a draft of the decree circulated, talking about a possible closure of most of Northern Italy since 9th, but this measure was overpassed few days later by the national lockdown. However, according to media, many people left the cities of Northern Italy towards the South. Those who remained in their location cannot move anymore until the end of the measure (not even among neighbouring municipalities and theoretically also within). At that moment of lockdown, Italy had about 12.000 official cases and more than 800 deaths. This first phase of lockdown lasted until May 5th, when a progressive relaxing of closures started, including industry and most of retail. Movements between regions remained prohibited until June 3rd, 2020.

The pandemic in Italy hit most of Northern Italy, and eastern Lombardy in particular. The outbreak spread from four locations: Codogno, Vò (Padua), Bergamo and Pesaro. In short other provinces were hit, in particular Milan and Brescia. Central and Southern Italy were less affected because the lockdown started before a significant number of cases occurred, while in the North lockdown was definitely late, when diffusion was enormous. This put some regions in the North among the ones within the highest per-capita death rates in the World.

6. The decline of local mobility

Local mobility decline has been studied using many different sources. Facebook data allow exploring the aggregate regional trends of the *Movement Range* metrics and the *Share of people staying at home*. The two measures, despite referred to different populations (the mobiles and the

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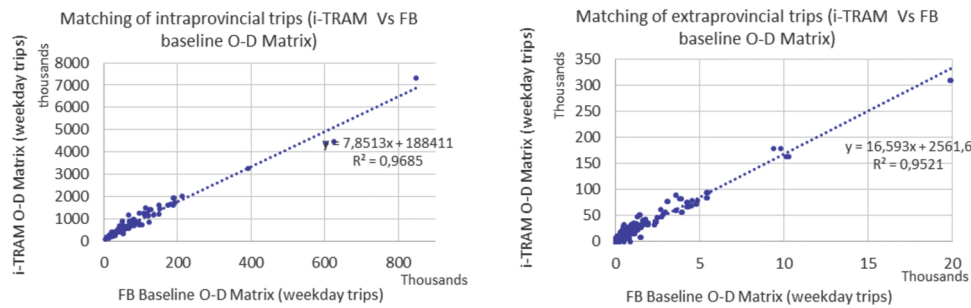[3] I-TRAM: https://metaplanning.it/atlante/

Fig. 4. Correlation - Facebook baseline movements Vs iTRAM model.

immobiles), appear correlated, as the more stationary a region is, the lesser is also the travel range. Fig. 5 shows the temporal variation of the *travel range* metric for the respective macro-regions. We observe how the implementation of early restrictions reduces the indicator in the North-West (Lombardy being epicentre region) and the North-East (Veneto being the second outbreak region) relative to the other macro-regions. The *travel range* has drastically reduced during weekends and we can note the sharp decline in the mobility behaviour after the official announcement of the lockdown on the 9th of March, 2020 after which the behaviour of all regions become analogous and convergent to each other. On the same graph we can also observe the *Share of people staying home* metric, which is nearly a mirror of the former, but with less macro-regional differences.

Further, the evolution of the share of people staying at home was different across regions. It is evident in Fig. 6 that the earliest affected Regions see a higher number of stationary users in the initial days of the outbreak, even before the lockdown. Lombardy which is the epicentral region of the outbreak experiences a 37 % higher than national average of users staying put followed by neighbouring regions of Liguria (23 %), Emilia-Romagna (15 %), Friuli-Venezia-Giulia (14 %), Piemonte (12 %) and Veneto (9 %). This is because many of the companies initiated the smart-working policy to avoid the diffusion of the virus. The regions of Aosta valley and Trentino Alto Adige which are popular ski destinations observe movements which might be due to tourists leaving the region. On the other hand, the central and the southern regions do not display a positive relative change of staying home until the official lockdown is announced on the 9th of March 2020.

7. The start of lockdown: the tale of an exodus (that did not happen)

The spread of the outbreak, but especially the national lockdown *announced* on March 9th, has pushed part of the population to relocate before getting "locked" into their current position. A recent research, applied in the totally different context of India (Denis et al., 2020), has shown quite clearly a dynamic of "escape" from cities towards the rural areas. More precisely, Indian rural population increased by 7 % while cities lost between 4 % and 11 % (from metropolis to small census towns). This effect is attributed both to the decrease of everyday/weekly commuting, but also – locally – to a consistent movement of migrant workers towards locations whose lower density was considered safer. This is the case of flows from Delhi to Northern India, and of Rajasthan, Odisha, Bangalore and Chennai towards smaller localities of origins of migrants.

In the case of Italy, media has given a lot of evidence to a sort of "exodus" occurred especially in the night of 8th–9th March 2020, when the last night train from Milano to the South had been "assaulted" by people that feared to remain in the northern capital. This tale has shaped significantly the debate on media and social media, assuming that the exodus has happened and the spread of potentially infected people from the North to the South would have caused further outbreaks and collapsed the health system.

The *Movement between Administrative Regions* dataset – that in Italy correspond to NUTS-3 Provinces – allows to verify if and to what extent such displacement happened. We have considered the entire period available, starting from February 24th to the end of May, after lockdown was relieved. Fig. 7 considers all movements between Italian provinces (i.e. excludes internal trips). During the first two weeks of the outbreak – before the lockdown was declared – the decrease with respect to baseline was limited (90 %). Only weekends' trips were well below the expected, showing that the behaviour was modified first for personal trips rather than for work trips. During the 1st week of lockdown, the mobility felt suddenly and reached level of 30 %/20 % of normal. Weekend trips basically disappeared until May. Interestingly, starting from end of March peak hours restarted to be visible (more precisely: the difference with baseline becomes smaller).

Regional differences are interesting too (Fig. 8). As expected, in the North interprovincial trips were already below the normal level since the beginning (also confirmed in Fig. 6), when in the South the difference with baseline is negligible. The macro-regional series start matching since March 9th, when central and southern regions are even slightly below the North-East. Later we see only some daily fluctuations, apart from the North-West – where the risk was higher, and the lockdown perceived as more severe. At the end of March, trips begin to rise again, ranging from 20 % to 40 % of baseline almost everywhere, including North-West. The end of lockdown added a 10 % step.

Mapping these flows shows again the progressive end of movements across the country, which in the 2nd half of March looks disconnected (Fig. 9). While initially we can recognize the usual patterns, with most of the flows within the North and along the coasts, plus some long-distance ones for example connecting Milan with Sicily, Already on March 9th they were substantially reduced. On March 24th the connections are basically absent, with the exception of some local trips among neighbouring provinces. Some connections between Rome and Sardinia and Sicily remain, probably connected with cargo movements.

By means of these observations, we can also verify if there were anomalous trips between the North and the Centre and South, especially at the instance of declaration of lockdown, as perceived by public opinion. Fig. 10, for example, plots the outgoing trips from the entire Lombardia[4] to the rest of the country. Not all destination regions are represented since there no OD pairs with more than 10 trips (which is the threshold of the original data). Emilia-Romagna and Piemonte account for the largest flows, which is natural being at the same time large and neighbouring. Typically, during weekends these flows fall, as leisure connections are more limited than working ones. To the contrary, in direction of Liguria, Val d'Aosta and Trentino Alto Adige – despite on a different scale – we see some increase during weekend, starting Friday 6th March and the following Saturday. The highest point of these flows is around 250 users, which should correspond to approx. 5000 people, per

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[4] Lombardia is the largest region (10M inhabitants), the most hit and the one from where media described the exodus. Figures from other regions were even less significant.
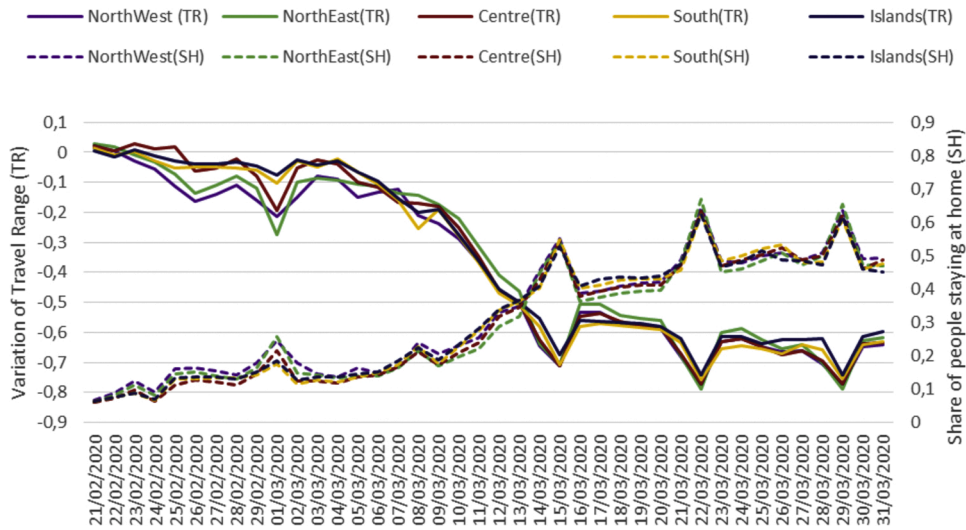
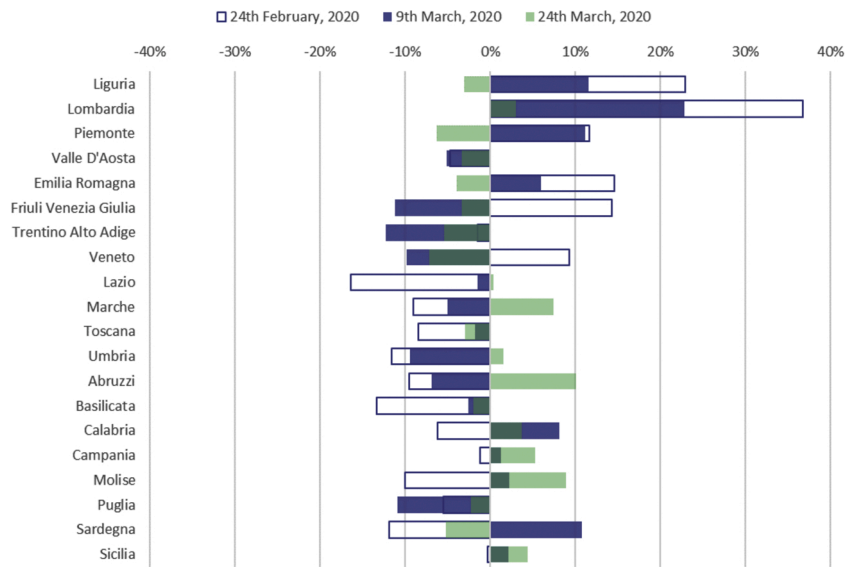**Fig. 5.** Relative number of total tiles for Italian macro-regions (TR: Travel Range, SH: Stay at home).

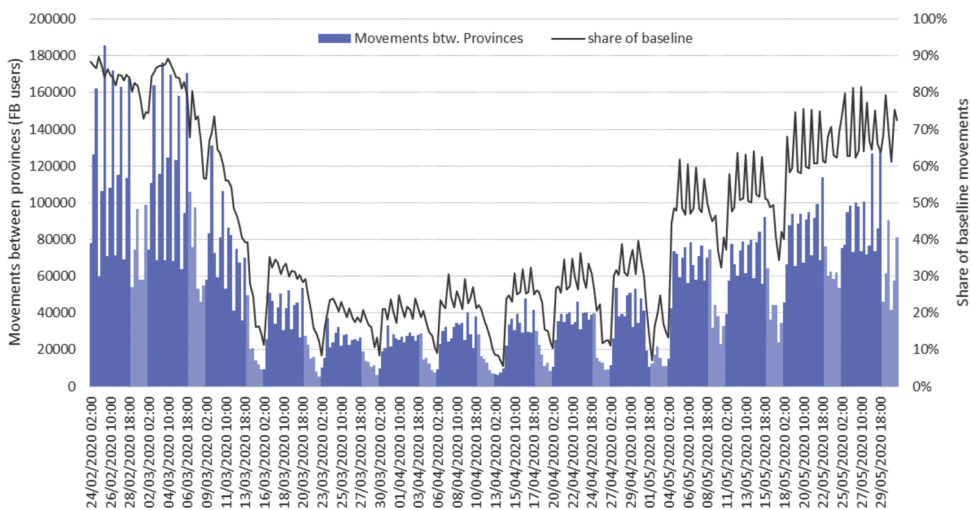**Fig. 6.** "Staying Home" relative change with respect to national average for regions.

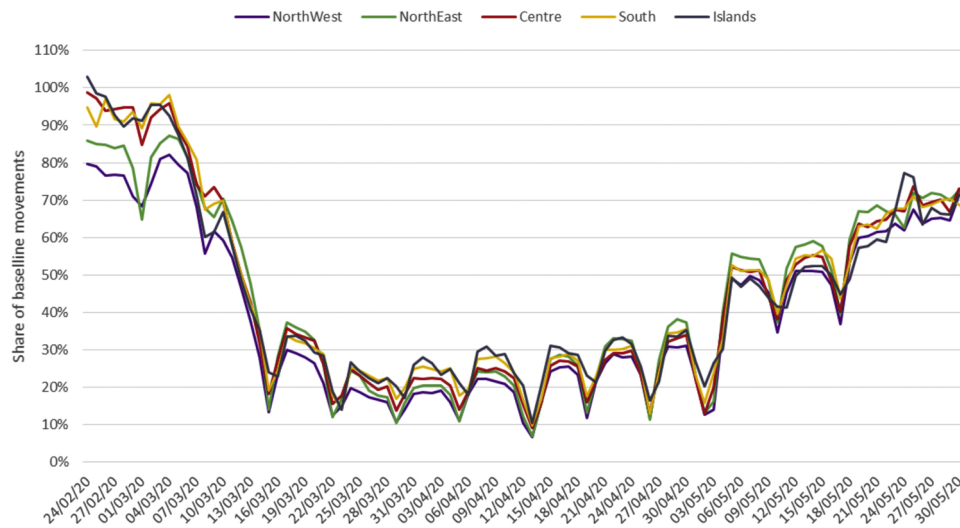**Fig. 7.** Total movements between provinces (NUTS-3) and share of baseline.

Fig. 8. Total movements between provinces (NUTS-3) grouped by macro-regions. Share of baseline.

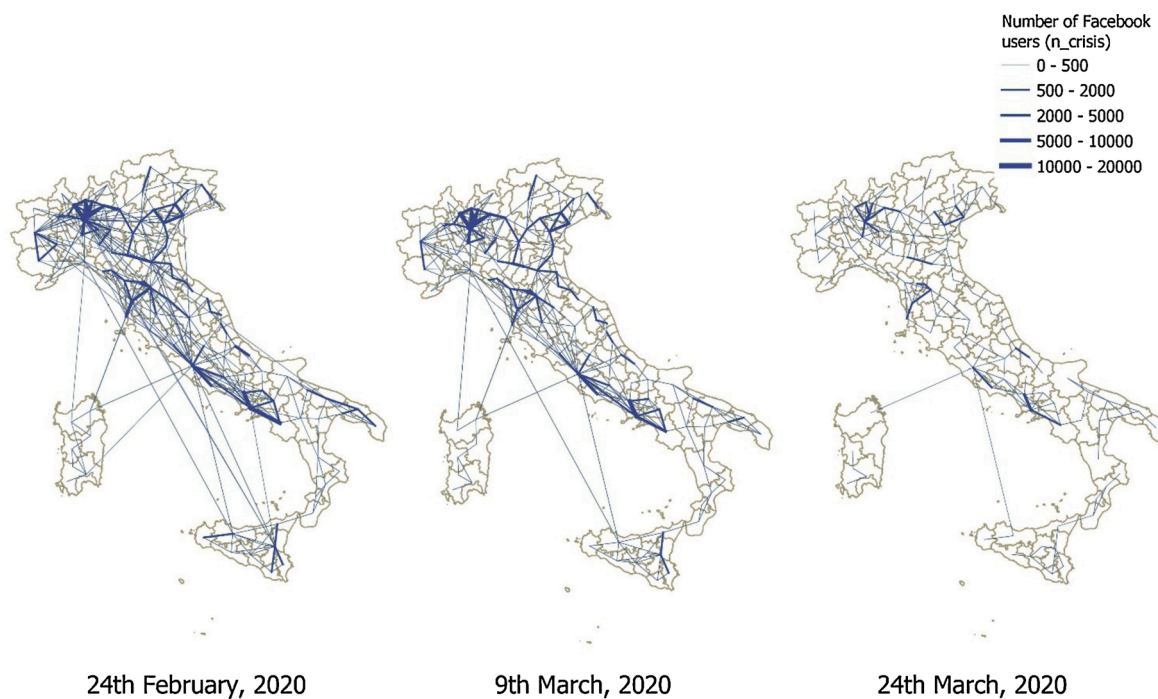24th February, 2020   9th March, 2020   24th March, 2020

Fig. 9. Interprovincial flows before and during lockdown.

day per region. Therefore, in conclusion, we can affirm that, even from Lombardy, no significant pour of population from North to South or elsewhere can be observed or is in the order of thousands of people.

8. Away from cities, away from contagion

After showing that no significant exodus occurred, it is more interesting to verify what has been observed elsewhere, that is if cities have emptied and where population has moved: far away, in the periphery, towards second houses at the sea or countryside or abroad (tourists or expats/migrants and the corresponding return of Italians from abroad).

In this case we use the *tile-level Facebook population data*. At the national scale tiles measure approx. 4800 m of edge and aggregate more basic tiles. The users present during crisis are compared with the baseline calculated on the presences during the 90 days prior to the event (in this case 24th of February 2020). As already underlined before, also this

data is not statistically representative and cannot be properly expanded to the entire Italian population but is very meaningful to show trends and to describe the behaviour of the large subset of population. Overall, the dataset includes about 3.3–3.4 Million people, corresponding to about 6 % of Italian population (but including also non-Italians temporarily present in the country).

We aim at responding to two basic questions:

1) Can we observe a significant regional relocation, especially between North (where the outbreak started) and the Centre/South, not catch by *Movement* dataset?
2) Or is there a relocation between dense cities and low-density areas, meaning either countryside, remote areas or simply second houses areas and seaside?

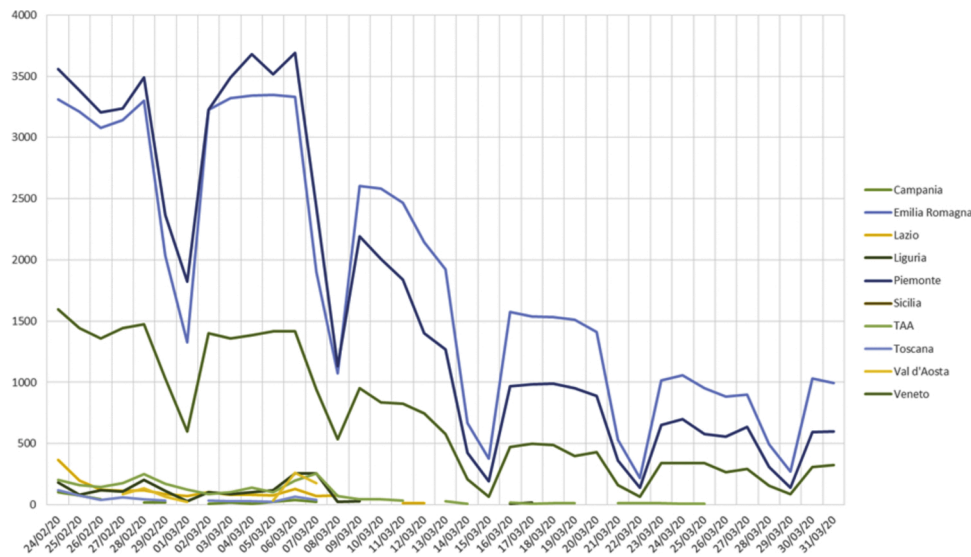To do that, we work at the tile level to produce difference maps and

Fig. 10. Total interprovincial movements from Lombardia to the rest of the country (internal trips in Lombardia excluded).

then we attribute every tile to the corresponding region (NUTS-2 level) and to the official classification of core and remote areas in use in Italy (called SNAI: Carrosio, Giovanni, Lucatelli Sabrina, and Barca Fabrizio, 2014)[5] . We work using the night-time slot (10 P M to 6AM), to avoid measuring the effect of commuting.

The first relevant result is related to totals. Differently from India – where total population was constant (Denis et al., 2020) – in Italy during the analysed period we observe Fig. 11 a significant -4 % decline in population starting from March 10th (after the 1st day of lockdown). In 3–4 weeks, this figure rises again. Our interpretation is that initially foreigners and especially tourists left the country (we will go back on this later), and later Italians abroad succeeded to re-enter.[6] The figures of the 28th April are the most interesting as represent a sort of picture freezing the position of Italians during lockdown and has been used in Fig. 2 as a reference to calibrate the sample matching it with census data (typically biased by commuting and temporary touristic presences).

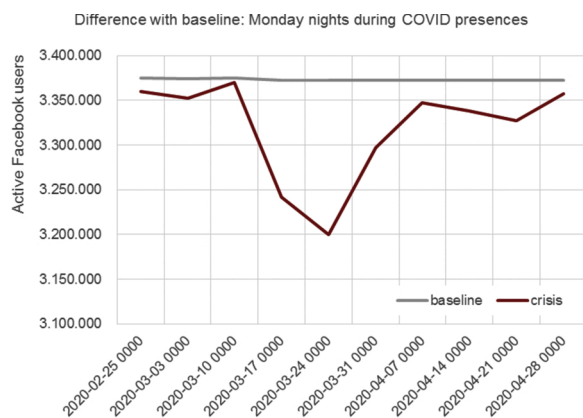To respond to the first question, if there was a significant relocation

Fig. 11. Total population observed during night-time (10:00 PM of Monday to 6:00 AM of Tuesday), referred to baseline.

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[5] The six classes are: Hub, Inter--municipal, Outlying, Intermediate, Peripheral and Ultra-peripheral. The classification is a service-based accessibility indicator, based on three variables: time to access high-schools, hospitals and main train stations.

[6] It must be highlighted that during lockdown airlines and train stopped operations and returns were managed by the Ministry of Foreign Affairs.

between regions (invisible in the *Movement* figures of Section because spread across many OD pairs below the threshold), we attribute the population tiles to regions, as in Fig. 12. With few exceptions, population of regions is basically constant. Only Valle d'Aosta and Trentino Alto Adige lose a significant share of population (around 10 %). This figure can be easily explained noticing that they are small mountain regions where the previous weeks were the full winter ski season.

Fig. 13 gives the absolute numbers. Lombardia and Lazio (the regions of Milano and Rome, respectively) lost 5–10000 Facebook users (which should correspond to approximately to 80–160000 persons). Another 5000 leave Trentino-Alto Adige, most likely Italian and foreign tourists. Remaining regions show variations between 0 and 3000 users, with central ones (Liguria to Abruzzo) gain population and Southern regions (Molise to Sardegna) lose some. Regional differences, overall, say that we cannot observe significant displacements, especially from North to South, except the sudden end of the ski season in the Alps.

Fig. 13 is useful in responding to the second question, if there was a relocation from cities to "outside", whatever this means. Following maps will be more detailed in this, but the national classification of remoteness can be used for an aggregate vision. Again, with the exception of the two small Alpine regions where remote areas that get empty are ski resorts, the pattern is a clear escape from cities, in particular the "poles" or "hubs" (usually provincial capitals and surroundings that lose 4.1 % of their population), in the direction of *Intermediate* territories (that gain 1.8 % of population), that could be described as the mid-density non-urban areas. The three peripheral classes (D to F) gain population, but in the order of few thousands overall. This pattern means that the loss of population of cities must be attributed to the lack of commuters (daily or weekly) that now stay at home within cities commuting areas, and limitedly to the movement of people towards remote areas.

Fig. 14 represents the first week of the outbreak (night between 24th and 25th February 2020). It clearly shows that there is a fall in population mainly in some cities in the North. Urban areas of Emilia Romagna, Tuscany and central Italy do not show any decline in presences, as well as most of the South. Rome (out of map) and Florence are more crowded than February, sign of the start of the city-focused spring touristic season.

During the peak of outbreak at the end of March (Fig. 14, above), the fall of population is the largest in *all* parts of the country. All "poles" got emptier, but almost nowhere population significantly increased, including remote areas. Again, this shows that there was not a pouring of population from one to another (very few "green" tiles), but a net loss, particularly pronounced in cities. It is interesting to notice the dramatic
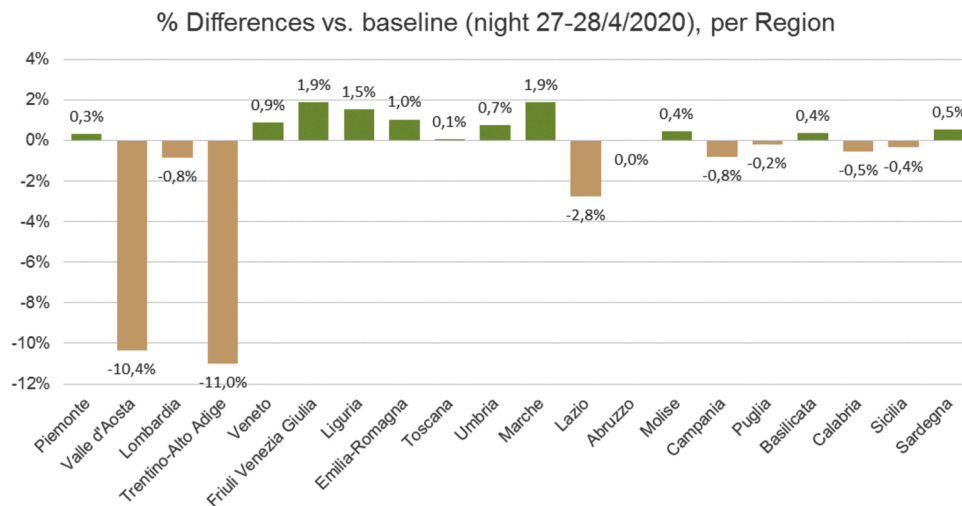
Fig. 12. Percentage difference between crisis and baseline observation, by region. Night between 27 and 28 April 2020.
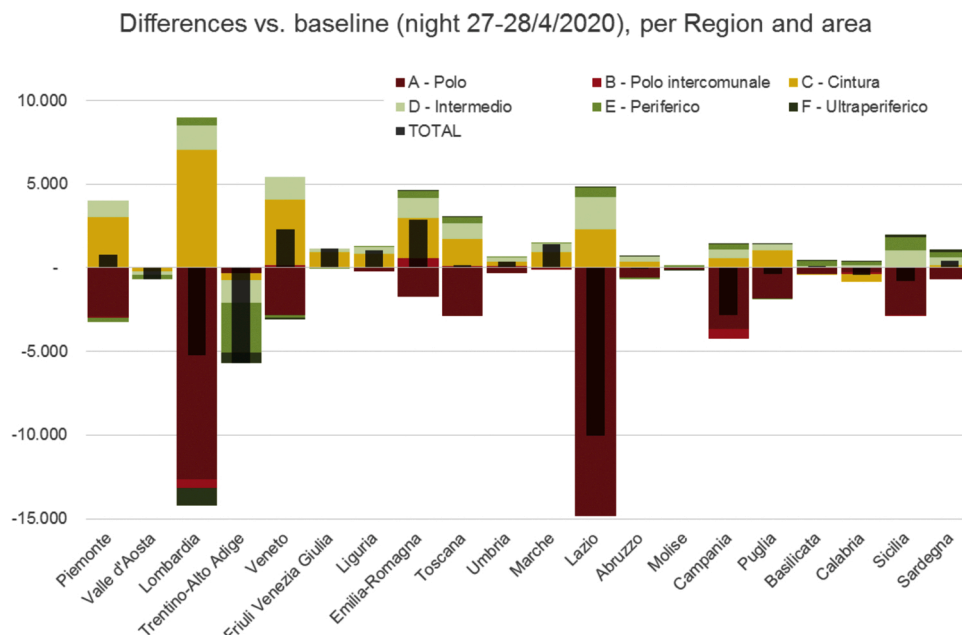

Fig. 13. Difference between crisis and baseline observation, by region and by SNAI classes. Night between 27 and 28 April 2020.

decrease of presences in Trentino Alto Adige and Lombardy valleys, from where all ski tourists departed.

Finally, the most stable period is the night of 27th–28th April 2020, shown in Fig. 15. Most of Italians abroad returned and most likely occupied their place of origin. Cities are totally blocked – no economic activities – with their resident population locked in. Here we can appreciate that, with few exceptions, the largest population increase is in urban belts (around Milan, between the cities of Veneto, along the Adriatic coast, between Florence and Pisa, around Rome, Naples and Bari. In other words, the most inhabited part of Italian territory out of cities.

There are some exceptions and they often belong to the areas – not all, however – where second houses concentrate. For example, as mapped in Fig. 16 filtering tiles with an increase of more than 20 Facebook users, some well-known touristic sites appear, such as Liguria coast

between Genova and Santa Margherita; the Versilia area and part of Tuscan coast; the "litorale romano" (the beaches south of Rome); Ischia, Costiera Amalfitana and Lago Patria near Naples. The remaining tiles all belong to urban belts.[7]
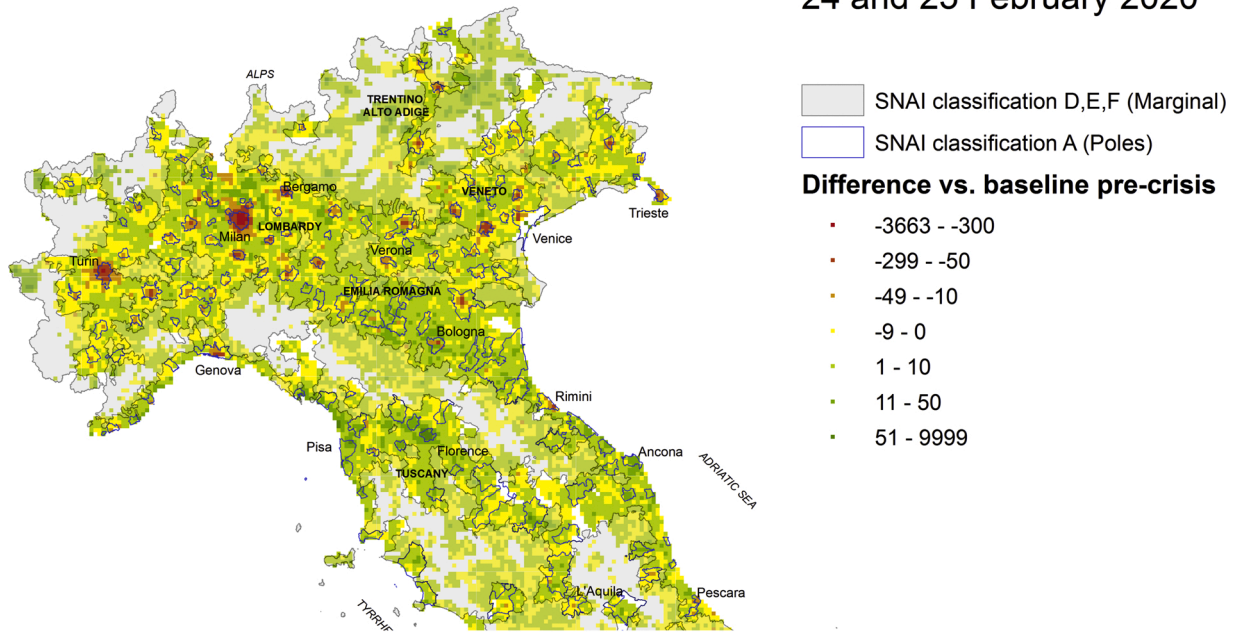
9. Conclusions: COVID-19 and possible impact on cities

9.1. Summary of conclusions

The COVID-19 outbreak had (and will have) enormous consequences in the mobility of entire countries, including country-scale lockdowns. Italy was the first-hit country in Europe and among the ones where it resulted more severe. In this paper we provide an in-depth analysis of mobility during COVID-19 first outbreak and lockdown in Italy using the data provided by Facebook Data for Good programme. These datasets

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[7] The area of Cassino, well visible, should be an effect of the baseline as documented by data developers.
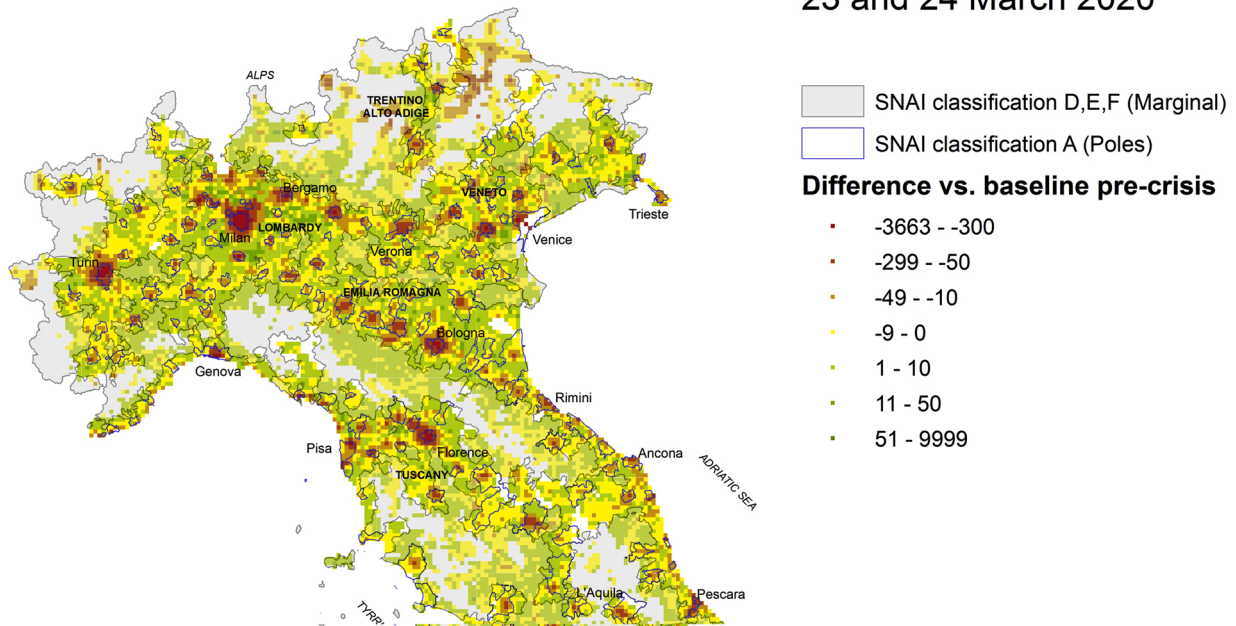
Fig. 14. Population difference vs. baseline. Nights between 24 and 25 February 2020 (first week of outbreak) and between 23th and 24*th* March 2020 (outbreak peak).

are used to trace almost real-time movements and presence of people during disaster and disease events.

In this work we mainly tried to answer to three research questions. The first one is how much and to what extent people "stayed at home" before, during and at the opening of the lockdown. Despite the media narration of people ignoring the lockdown, data clearly show since March (the lockdown was declared on March 11th) the share of people moving and the range of movement fell dramatically to a nearly physiological level (supplies, health workers, necessary trips).

The second point was about the movement of population just before the lockdown, especially from the northern provinces, the most hit, and central and southern Italy. This movement happened very marginally,

with few thousands of people crossing the country to avoid remaining locked. Some non-local trips remained, but they are substantially confined to neighbouring provinces. Long-distance trips remain nearly always below the measurement thresholds.

The last aspect deals with the location of people during lockdown. The most visible phenomenon is the fall of population in largest cities, starting from the North but soon occurred also elsewhere. People did not relocate (except few, of course) in marginal areas, but basically concentrated in the rest of urbanised areas. This fact has a twofold explanation: commuters and city users stopped moving into urban poles and out-of-home workers went back to the place of origin, which is often inside the region.
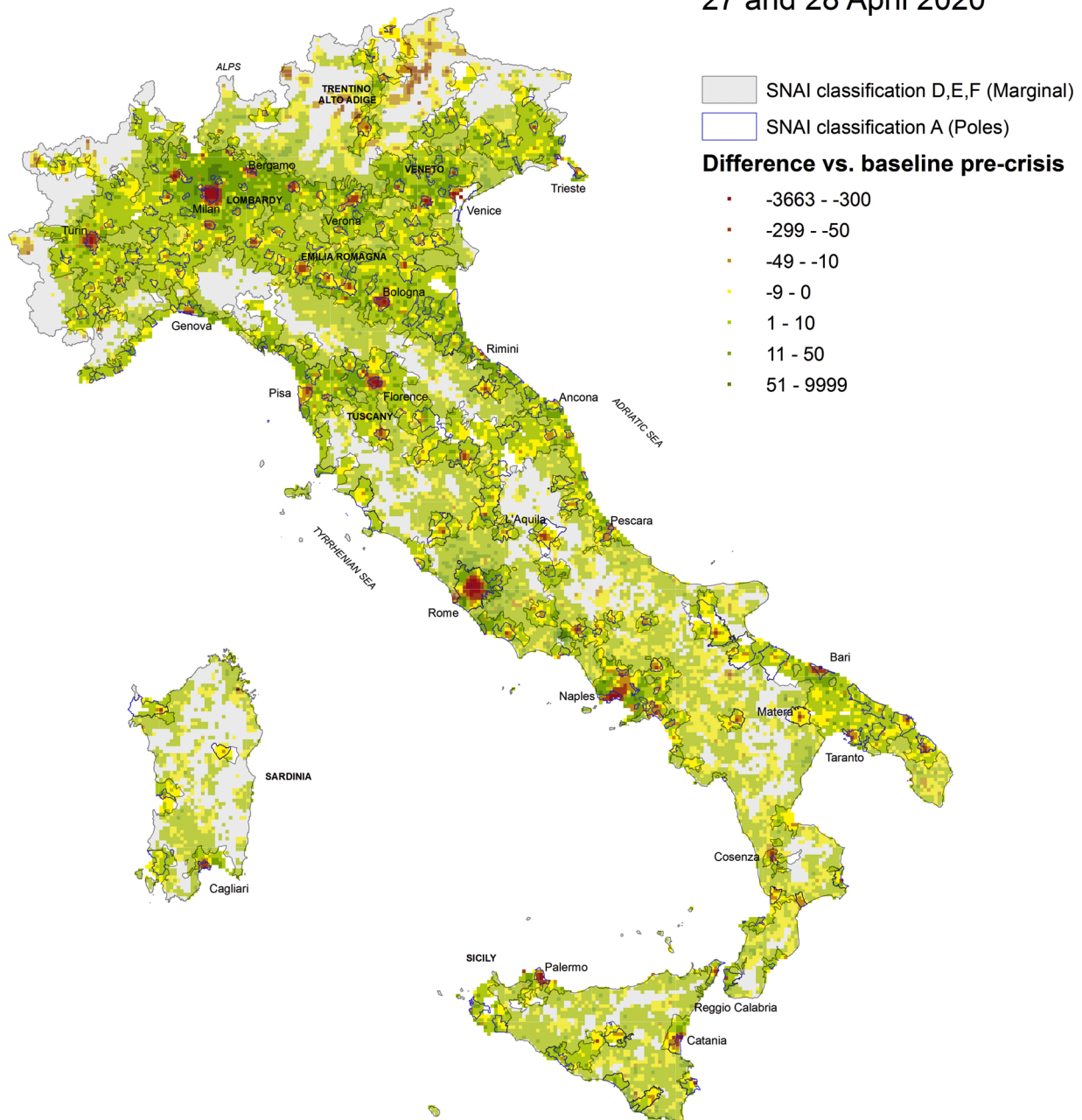
Monday night between 27 and 28 April 2020

Fig. 15. Population difference vs. baseline. Night between 27 and 28 April 2020.

9.2. Possible impacts on the future of cities

The debate around the role of cities and their design in the post-COVID world has been intense since the beginning of the crisis. While just few believe that future will return to a business-as-usual scheme, we can distinguish two alternative visions.

On the one side, someone predicts that cities will disappear in the current form of super-dense concentrations of activities and people. These months have shown that smart- or just remote-working will enter in our lives pervasively, letting people be productive even far from dense offices. What during these months has been a way to stay *out from the madding crowd* and prevent infection, is doomed to become the norm. In the case this will happen, where is people going to move? The indication of these months is that remote areas are less attractive with respect to

urban belts or vacation areas such as coasts (which are usually densely built, in Italy). Urban belts and intermediate territories (of which Italy is rich: small towns and low density areas, not necessarily unreachable) attracted more people than isolated areas, also in relative terms.

Opposed to this vision, those who believe that cities will be again at the centre of development once the storm has passed. Benefits of concentration are such – and sometimes necessary, like for hospitals, fairs, business, etc. – that cities will just be redesigned by COVID (by smart-working) (Sharifi & Khavarian-Garmsir, 2020). More space will be requested by residence and less by offices, possibly finding a new equilibrium. Cities should reconvert into hubs of activities, not necessarily a place to live all week long. A necessary condition, in this context, is a further push towards the quality of life and of city space, but also in terms of city health and resilience to disasters (Wang, 2020). Policies put
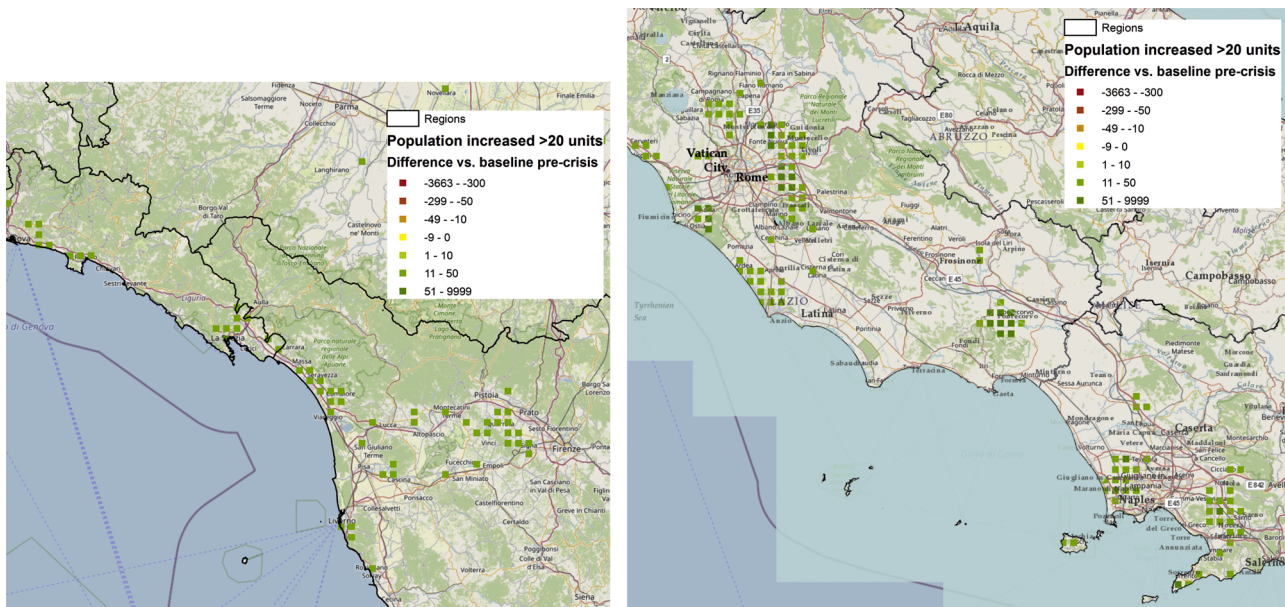
Fig. 16. Population difference vs. baseline higher than +20 users. Night between 27 and 28 April 2020. Detail of the Levante Ligure and of Tuscan coast (left) and of the area between Rome and Naples (right). Background map: Openstreetmap.

in place now, as a way to alleviate the problems of distancing (bike lanes to lighten the pressure of car mobility, open-air activities, outdoor restaurants and pubs to reduce infection risks, etc.), are expected to become the new normality after the crisis.

This evolution is just started, but our data showed that cities were slightly emptied, but never became "empty", even in the darkest hours of lockdown. Just a fraction of people was actually able to leave the city, and not just for the legal restrictions. Simply, many jobs are place-specific as well as many services and functions. Therefore, the bucolic vision of a return to the mountains and countryside, abandoning the illusion of the benefits of dense cities, is something that – if going to happen – could be slow and limited to an elite of intellectual workers for whom smart-working (or self-working) is feasible and at the same time quality housing space is available.

In the case of city-exit, however, the impact on urban mobility is going to be significant. In case of a shift to urban belts, commuting will become longer but less frequent, relieving the pressure on public transport, but not necessarily reducing total mileage driven. Also infrastructure could become a problem if the subtle equilibrium between private and public transport will break. In case of a shift to remote areas, commuting will reduce, but many other trips could become necessary, starting from the simple issue of everyday shopping. New forms of commerce will develop, but no one knows if this will be beneficial or not for mobility.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.scs.2020.102616.

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