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Did Liberal Lockdown Policies Change Spatial Behaviour in Sweden? Mapping Daily Mobilities in Stockholm Using Mobile Phone Data During COVID-19

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Abstract

Sweden had the most liberal lockdown policies in Europe during the Covid-19 pandemic. Relying on individual responsibility and behavioural nudges, their effectiveness was questioned from the perspective of others who responded with legal restrictions on behaviour. In this study, using mobile phone data, we therefore examine daily spatial mobilities in Stockholm to understand how they changed during the pandemic from their pre-pandemic baseline given this background. The analysis demonstrates: that mobilities did indeed change but with some variations according to (a) the residential social composition of places and (b) their locations within the city; that the changes were long lasting; and that the average fall in spatial mobility across the whole was not caused by everybody moving less but instead by more people joining the group of those who stayed close to home. It showed, furthermore, that there were seasonal differences in spatial behaviour as well as those associated with major religious or national festivals. The analysis indicates the value of mobile phone data for spatially fine-grained mobility research but also shows its weaknesses, namely the lack of personal information on important covariates such as age, gender, and education.

Keywords COVID19 · Urban form · Big data · Spatial mobility · Temporal analysis

Highlights • Shows that the less coercive lockdown policies of Sweden led to large falls in daily spatial mobility during the COVID-19 pandemic in Stockholm.
• Demonstrates that compliance, as measured by sustained falls in mobility, persisted through the pandemic.
• Indicates lesser falls in spatial mobility from baseline during holidays.
• Demonstrates that socio-economic context, land use, and urban form were important in shaping these mobility declines, with affluent neighbourhoods on the edge of the city recording the greatest decreases.
• Indicates that mean mobility reductions were not achieved by all people moving less on average but by one substantial group of people hardly moving at all after lockdown whilst a minority remained closer to pre-pandemic mobility levels.

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Introduction

One response of many to the COVID-19 pandemic was to restrict interpersonal contact to reduce the transmission of the virus. Many countries therefore instituted lockdowns of varying degrees of severity, limiting leisure activities, social gatherings, and recommending that people work from home wherever possible. The outcomes of the pandemic on spatial mobility have been noted at different spatial scales and in different domains, ranging from internal migration/residential mobility (Fielding & Ishikawa, 2021; Willberg et al., 2021), daily activity ranges for whole countries (Hernando et al., 2020, 2021), or for cities (Toger et al., 2021; Müürisepp et al., 2023). Findings include a decline in inter-regional migration and its redistribution to more rural areas (Willberg et al., 2021), decreasing values of activity-space indicators, such as average radii of gyration (Hernando et al., 2020, 2021), decreases in commuting especially at peak times, and the individualisation of transport modes (Toger et al., 2021). What is less known is how durable these mobility changes have been and still are, considering the spatial and sociodemographic composition of different parts of the urban landscape.

This paper aims to take this emerging literature further by comparing and analysing spatial mobility patterns in Stockholm for selected dates in 2019, 2020, and 2021 to measure the impact of policies throughout 2020 and the early months of 2021. This gives insights into the durability of health restrictions on daily activities. In concentrating on Stockholm, we consider the experience of residents of the capital city with the third highest rate of COVID-19 deaths in Europe (Warren et al., 2021) and also investigate population responses to Swedish policy, which differed from many other European countries with its emphasis on individual judgement and responsibility, and 'nudges' rather than more directive government action. It is useful to assess whether this policy framework led to long-term changes in behaviour to understand better how populations respond to government advice. It also adds to the literature by considering the diversity of spatial mobility changes by residential location and socioeconomic context. This issue is important given the inequalities in COVID mortality in Sweden by age, wealth, and ethnicity (Drefahl et al., 2020), which raise the possibility that the residents of the disadvantaged parts of the city did not isolate as effectively as their more affluent peers. The questions we seek therefore to answer are: 1) Did the relatively liberal Swedish policy towards lockdown lead to long lasting changes in population mobility? 2) In Greater Stockholm, do we find geographical patterns of mobility change that are related to urban form, land use, and distance from the urban core? 3) Do daily spatial mobility changes reflect the socioeconomic and demographic contexts of neighbourhoods? 4) and, lastly, how far did spatial mobility vary through time?

We use the MIND dataset, which contains pseudonymised phone-usage records of 10–20% of the Swedish population, to create a panel representing phone mobility patterns such as area of gyration, activity ellipse, and maximum distance travelled. The phone data is treated on a daily basis and aggregated to the third Thursday of the months January, March and October in 2019, 2020 and

2021 (only January and March in 2021). In addition, public holidays are included in the analysis to examine changes in spatial mobility when population responses to policies and nudges potentially alter. To quantify spatial mobility patterns against a set of contextual and socioeconomic influences, we employ a random-effects model. The contextual and socioeconomic variables are extracted from OpenStreetMap (OSM) and the PLACE database (longitudinal full population register database), respectively for each phone km^2 unit in the MIND dataset.

The paper is organized as follows: in the next section, literature describing mobility, the effects of COVID-19 on mobility and the Swedish scene is discussed. In the Data and Methods section, the data and methods are described and in the results section the results from the analyses are presented. Finally, in the final section a few concluding remarks are made.

Literature Review

Factors Shaping Human Mobility

It is a commonplace that human interactions across space over several activity domains are shaped by a distance power law. The interaction between towns as expressed by migration flows was noted by Ravenstein (1885) as being greater between larger and nearer settlements, and this has underlain a tradition of gravity and spatial interaction migration models (Poot et al., 2016). Distance decay appears to be fundamental; it shapes activity profiles (Haynes, 1974), and is in essence the cornerstone in the first law of geography (Tobler, 1970). The same observation has been made about daily activities such as commuting with considerable discussion about the formulation of the distance-decay parameter (De Vries et al., 2009; Östh et al., 2016) but with the underlying realisation that people interact more often with places close to them and tend to stay near home. This is generalizable to other types of daily human activity. Xu et al. (2018), for example, found that daily activity spaces in Boston and Singapore conformed to a truncated power law with people returning to the same places frequently as did Wang and Taylor (2014).

Distance decay and the tendency to remain near home thus shape activity spaces. However, activity spaces are also modified by and are contingent upon urban form and on socioeconomic characteristics. Xu et al. (2018) observed that mobile phones from richer areas covered a greater spatial range in Boston than poorer phones, but the reverse was the case in Singapore. This was explained by richer neighbourhoods being located at the edge of the Boston Metropolitan Area in areas with sparser services and job opportunities, necessitating greater activity spaces, whereas in Singapore high-income areas were located in the urban core, and thus nearer to opportunities. Hu et al. (2020) also finds that urban activity space sizes are related to socioeconomic characteristics and location. Higher income and education, and distance from the Central Business District (CBD) are related to bigger activity areas, whilst lower income and membership of a minority group are linked with smaller areas. This accords well with the migration and commuting literature where higher education and higher income are positively associated with longer migrations and longer commutes but where locational context also plays a powerful role.

Spatial Mobility and COVID-19

Given the background outlined above, it would be expected that there would be pre-pandemic differentials in daily spatial mobility in Stockholm; residents from suburban areas might be more mobile than those from the inner city, for instance, those from areas with higher-qualified residents should be more mobile on average than those with less-qualified residents. These generalities, of course, are subject to the unique spatial structure of Stockholm, its specific configuration of transport routes, opportunities, land use, and social geography. Swedish government policies to reduce physical human interactions in 2020 and 2021 therefore operated in an already uneven geography with differential experiences of daily spatial mobility.

The literature suggests that the onset of the pandemic and government lockdown responses led to marked reductions in spatial mobility in other countries such as the UK, Spain, and the USA, across a variety of activity domains (Cot et al., 2021; Hernando et al., 2021; Toger et al., 2020; Shuttleworth & Gould, 2023). It also indicates that these reductions were experienced unequally geographically and socially (Müürisepp et al., 2023; Lee et al., 2021). It was considered that larger cities and regions with more qualified and skilled workforces would be better able to lockdown (because of a greater capacity to work remotely) and also better placed to weather lockdowns economically for the same reason (OECD, 2020). This was observed, for instance, by Shuttleworth and Gould (2023) using place-aggregated Google Mobility data in the UK and also by Hernando et al. (2020) using phone-level data in Spain. These Spanish findings are particularly telling as they show that pre-pandemic phones from poorer areas had an average radius of gyration of 8.1 km as against 6.9 km for phones from richer areas (note that in this national context it is residents of poorer areas who are mobile than those from richer places) and which fell, during the pandemic, respectively to 3.3 km and 900 m. The implication in this Spanish case is that although everyone became less mobile, phones from more affluent areas – and thus owned it must be assumed by better-off people – changed their behaviour more sharply. These income and educational differentials are replicated in the USA where mobile phone studies demonstrated that those originating in high-income neighbourhoods were better able to reduce daily spatial mobility and to distance socially than those from poorer places. These studies indicate general Covid-related falls in spatial mobility but which are greater for more affluent areas. They reveal little about causality; however, it is probable that there are greater prospects for teleworking for higher-skilled and educated people (consider the case of those involved in higher education as students or staff, for instance) whilst other jobs which are typically less-skilled are less amenable to remote working.

It is highly likely that these spatial differentials at least contribute to the patterns of Covid morbidity and mortality by social background and location. Hernando et al. (2020) argue that a radius of gyration at 70% or less of the pre-pandemic level was significant in reducing Covid infections. If this can be generalised to other national contexts, people (or places) unable to effect and maintain physical isolation would be far more vulnerable to the spread of Covid than those more affluent people (and places) who were able to reduce their spatial mobility.

This discussion adds to, and refines, the four research questions identified at the end of the introduction. The mobility reductions seen outside Sweden in the UK, USA, and Spain (all with different policy responses to the more liberal Swedish situation) mean that it is important to explore whether the Swedish approach led to long-lasting falls in mobility across Stockholm. The evidence that more highly-qualified and high-income people and areas saw the biggest mobility falls elsewhere suggests that the same patterns ought to be observed in Stockholm. Finally, the importance of urban morphology that was identified, (the unique layout of an urban area), means that an analysis of Stockholm contributes to an understanding of this diversity.

Setting the Swedish Scene

During the Spring of 2020 as COVID-19 spread across Europe, governments aimed to reduce its transmission to protect health providers from being overwhelmed, to keep the numbers of deaths to a minimum, and to give time for vaccines to be developed. Since vaccines only became available at the very end of 2020, the main available policy lever was to reduce inter-personal contacts. Despite the common aim, governments made different policy responses, emphasising varyingly compulsion, personal responsibility, legislation, and recommendations. These differences were a consequence of varying national political cultures and diverse institutional frameworks (Andersson & Aylott, 2020). Sweden attracted much attention as it was an outlier when compared with its Scandinavian peers and a basket of European comparators. Policy in Sweden tended to nudge and recommendation with an emphasis on individual responsibility. Unlike, for example, in the UK, where politicians made decisions, the response was led by the Public Health Agency (PHA) under its head, Anders Tegnell. It sought to protect the elderly and the healthcare system (Granberg et al., 2021; Warren et al., 2021) and its objective was mitigation rather than suppression. The PHA was sceptical of the need (and effectiveness) of lockdowns and believed that Sweden was well placed to weather the pandemic with its low population density, small households, and good public health (Granberg et al., 2021). Furthermore, it was considered that voluntary measures that were based on individual responsibilities would be less onerous and far more sustainable. A side effect of mitigation would also be some herd immunity by the time of any Autumn second wave (Warren et al., 2021). Coupled with a degree of fatalism – COVID-19 was viewed as highly transmissible and would spread anyway– this set Sweden on a different path, and one that fitted with a Swedish national sense of exceptionalism.

It would be wrong, however, to say that Sweden adopted a laissez faire policy. In March 2020, senior schools and universities turned digital, (although primary schools remained open), home working was encouraged, over 70s were advised to self-isolate, only essential travel was advised, public gatherings were restricted to 50 or less people, and visits to care homes were stopped. Restaurants and bars were allowed to stay open (unlike in many other European states) but with precautionary measures and distancing in place. As in other countries, care home residents, and over 70s suffered a disproportionate number of deaths (Granberg et al., 2021). Furthermore, the most vulnerable members of society (the poorer, the less educated, and immigrants) experienced disproportionately high levels of mortality (Drefahl et al., 2020). Restrictions had to be tightened on November 16th and 22nd 2020, after some relaxation over the Summer, in the face of a rapidly mounting second wave – no sign of herd immunity – with even tighter restrictions on December 18th 2020. It is noteworthy that Stockholm was the third hardest hit European capital city after Madrid and Brussels (Warren et al., 2021). The second half of 2021 saw increased incidence rates due to Delta and Omicron variants of COVID19.

Data and Methods

The data used comes from the MIND database located at Uppsala University. MIND contains phone-usage records of between 10% and 20% of the Swedish population[1]. The data contains only pseudonymised data records, and its usage is guided by an ethics application approval. Ethical restrictions mean it is only possible to analyse daily data for a selection of days rather than all dates. The database contains data for long time periods, but detailed data describing the phone usage is therefore only analysed on a daily basis (24 h), with the results aggregated for a selection of dates.

This procedure was used to create a panel containing pseudonymized IDs representing phones, and calculated outputs describing phone mobility patterns (such as area of gyration, maximum distance travelled) for each phone for selected dates in 2019, 2020, and 2021, but without information about the duration or spatial orientation of any trip, and without comparing trajectories or temporal activity patterns between a wider sample of days (for ethical reasons). The pseudonymized records may be beneficial from an ethical perspective but due to the lack of user information collected by the phone company (e.g. age, gender, education, ethnicity), we cannot match phone behaviour to individual user characteristics and so we are dependent on the use of external data sources for the generation of probabilistic co-location-based user characteristics. The probabilistic matching procedure means that the ecological fallacy will lead to the misclassification of phones in some instances when, for whatever reasons, the phone owners do not share the average characteristics of the area. However, due to nature of the data and the legal frameworks such as GDPR, a more accurate matching process is not possible and the fine-grained spatial scale of the analysis lessens the risk of the ecological fallacy than if we were forced to use much larger areas. In "Contextual and Socioeconomic Variables" section, the probabilistic matching procedure is described in more detail.

Data Selection and Variable Creation in Daily Phone Datasets

To study in mobility patterns over time, detailed records depicting location and time are needed. The accuracy of the data is dependent on the density of GSM-antennas,

[1] Percentages vary over time, and the exact numbers cannot be revealed due to agreements with the data provider.

and the densest distributions of antennas are found in or near the metropolitan areas. To capture mobility, we created two sets of geographies; the first-level geography covered the greater Stockholm region, including neighbouring larger urban areas such as Uppsala, the coast-line and rural areas, airports and smaller towns. Any phone that was active within this region was included in the dataset for that day. At the second level of geography, we selected all phones that had an estimated residence within a 50 km radius of the centrally-located Stockholm Main Railway Station. Within this radius, both urban, peri-urban and rural activities can be found and roads, public transport and almost all commuting takes place within this area. The second-level geography population was included in the statistical analyses conducted in this paper, and their mobility activities within the larger first-level geography was registered and used to create the phone mobility variables that are used in the paper.

The 11 dates in the analysis were chosen to describe longitudinal mobility trends for corresponding dates in 2019, 2020 and 2021. The selected dates were weekdays, Thursdays chosen as most typical, which represented normal times as a baseline (January and March 2019 and January 2020 and October 2019), times directly after the pandemic was declared (March 2020), dates in later phases of the pandemic (January 2020 and 2021, and March 2021), Easter holidays in 2019, 2020, and 2021, and dates when the lockdown restrictions were less restrictive (October 2020). Thursdays are the weekday that has least between-weeks variation in an analysis of mobile phone behaviour in Sweden (Toger et al., 2020), hence our choice of this day. These findings suggest that by choosing Thursdays to represent typical workdays we reduce the risk that observed mobility patterns are correlated to unusual events (holidays, main sport events, etc.).

For each day, the following variables were created separately for each phone: KM of origin, KM of destination (as midpoints in a 1 km x 1 km grid), Origin-Destination (OD) distance, radius of gyration, activity ellipse and length of major and minor axis of the activity ellipse. *KM of origin* and *KM of destination* were created using the same method. In an NDR dataset there is a registered link between each phone and an antenna providing service at all times. If there are several antennas in the vicinity, the phone will switch between antennas according to proximity, activity, and antenna load. By using the duration-weighted service at the different antennas within specific time-frames (00:30 – 07:20 for Origin, and 11.00–12.00 & 13.00–15.00 for destination) we calculate crude OD coordinates on km^2 level and use these as representations for place of home (origin) and day activity (destination). The *OD distance* variable is calculated as each phone's Cartesian distance between the estimatedcoordinates of origin and destination. The radius of gyration was computed following the procedure common to human mobility research using cell-phone data (Gonzalez et al., 2008; Pappalardo et al., 2015; Xu et al., 2018; Gauvin et al., 2021; Barbosa et al. 2018; Matekenya et al., 2021; Blumenstock, 2012; Hernando et al., 2020; Bachir, 2019; Kang et al., 2012). Conceptually it measures how far the individual "strays" from the centre of gravity of all locations for a specific period - normally a day. The daily radius of gyration was measured as follows:

Given an individual i's trajectory for a time window t (e.g. 2 h starting from midnight), comprising a set of locations $L_j(i,t) = (x_j, y_j)$, thus centre of mass is $L_c(i,t) = (x_c, y_c)$ where $x_c = \frac{1}{n}\sum_{j=1}^{n} x\_j$, $y_c = \frac{1}{n}\sum_{j=1}^{n} y\_j$, n is the number of locations for the user i at time window t, and L_j is the j-th location having coordinates of the position of the mobile phone antenna x_j, y_j.

Radius of gyration $r(i,t)$ of the user i at time window t is: $r(i,t) = \sqrt{\frac{1}{n}\sum_{j=1}^{n} d_{j,c}^2}$, where $d_{j,c}$ is the distance between position j and the centre of mass c of the user i in time window t. We approximate the distance to Euclidean distances because the coordinates are in projected coordinate system in metres (EPSG 3006 - SWEREF99 TM), so we use $d_{j,c} = \sqrt{\left(x_j - x_c\right)^2 + \left(y_j - y_c\right)^2}$. Thus $d_{j,c} = \left(x_j - x_c\right)^2 + \left(y_j - y_c\right)^2$ and it follows that

$$r(i,t) = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(\left(x_j - x_c\right)^2 + \left(y_j - y_c\right)^2)}.$$

The *activity ellipse* and length of *major and minor axes* were calculated using a standard deviational ellipse approach. The area constituted by one standard deviation of the coordinate observations was selected from the average coordinate midpoint made up the activity ellipse of the phone. The major and minor axes are expressed as the maximum and minimal Cartesian distance needed to reach the border of the ellipse from the average coordinate midpoint. The major and minor axes are useful to observe general mobility behaviours of each phone, where the length of axes can be used to indicate sizes of activity areas, and where the flatness and size of the ellipse can give an indication if the individual is moving to one or many destinations.

Data Aggregation and Panel Data Creation

For each day, the above listed variables were created for each phone, but far from every phone held data that can be used at a later stage in the analyses. Only active phones that are in the study area during both night and day will have coordinates that make it possible to locate a phone to a km^2 unit of origin and destination; and only the phones that are estimated to have origin within the 50 km threshold from Stockholm Main railway station are included in the regression analysis in order to exclude cross-city mobility. In order to ensure a balanced panel for analysis, we maintained consistent square kilometre (km^2) origins and destinations throughout each period of the study. This allowed us to minimize potential biases arising from changes in geographic coverage or composition, enabling a more robust examination of spatial mobility patterns over time.

Contextual and Socioeconomic Variables

For each phone-populated km^2 unit in the dataset, data was added describing the surrounding physical landscape, the sociodemographic composition, and the spatial relationships/distances to population concentrations, jobs, and city-centre. The variables are chosen to represent localized patterns of service, access to amenities, and population densities that influence the need of travel. For the **surrounding physical landscape**, the share of the area within a 500 m radius from each km^2 midpoint with the following features was calculated: *Green*, including all parks and other green public areas but excluding forests, fields or grazing areas; *residential*, including all parcels designated for residential activities; *industrial*, including all areas containing industrial productions, excavation sites, dump-sites and facilities for sewer and energy management; *water*, including lakes, sea, and streams and finally; *commercial*, containing all areas designated for retail. The calculations were conducted using ArcMap Pro, and data were retrieved from OpenStreetMap (OSM). The surrounding physical landscape variables are time-invariant variables.

To describe the **socio-demographic composition** of places, a k-nearest neighbour approach was implemented in which the population composition of the 500 nearest neighbours from each km^2 unit midpoint was used. These data, which are unrelated to the MIND dataset, come from the population register PLACE, available at Uppsala University. PLACE has geocoded information on socio-demographics for 100 m x 100 m grids. The following variables were created: *Riskr 500*, contains the share of individuals at least 70 years of age, officially classified as a risk-group during the pandemic; *highedu 500*, the share of individuals with a university degree, with greater opportunities to telecommute, and finally; *VM 500*, the share of individuals born in Africa, Asia or Latin-America. VM, or Visible Minority groups, have in Sweden been observed to have greater COVID19-related mortality rates compared to the average population.

To create the **spatial relationships/distances**, from each km^2 midpoint, the Cartesian distance needed to reach the 500 nearest individuals and the 500 nearest jobs was saved as the separate variables, *Dist 500* and *Job Dist 500*. The distance variables functioned as indicators of population density and indicated if commuting shorter or longer distances to jobs was necessary. The variables above were all created using EquiPop (Östh, 2014; Östh & Türk, 2020). The estimated home-coordinates are not used in any of the analyses and are not saved to the panel dataset, but the Cartesian distance between estimated origin and the main rail station in Stockholm is saved as *DistOJV*. Stockholm railway station is chosen because the station functions as a hub for a large proportion of communications in the region, but also because the centre of Stockholm has a high density of jobs and residences and is so very important as an origin and a destination. This measured the centrality of residence of each phone-user. Finally, the total events observed per phone was saved as a variable named *Events per phone*. The number of stored events (calls, texts, internet-usage, handover between masts, etc.) may affect the dependent variables and thus the event count is included as a countermeasure in the regressions.

Regression Framework

In the regression framework, we employ a linear random-effects model to estimate mobility changes in the Post-COVID period from the baseline and the interaction effects of neighbourhood socioeconomic characteristics, land use, and location. Note that a multilevel specification (see Türk & Östh, 2019; Teke-Lloyd et al., 2022 for examples) would produce the same statistics.

The main model is defined as follows:

$$M_{ij} = \beta_i + \gamma_j + \alpha C_{ij} + \gamma R_{it} + \delta S_{ij} + \mu D_{it} + \varepsilon_{ij} \tag{1}$$

where M_{ij} is the activity space or radius of gyration of phone i in date j, β_i and γ_j are phone and date fixed effects, respectively, C_{ij} are control variables such as events per phone, R_{it} indicate the composition of activity spaces in terms of land use such as fraction of green and water, residential, commercial or industrial fractions and S_{ij} are socioeconomic variables of the departure neighbourhoods such as the share of VMs, highly educated population, and risk groups (aged 65+), and finally D_{it} is distance to Stockholm Central Station. When studying the changes in mobility behaviour, we interact date-fixed effects with C_{ij}, R_{it} and D_{it}. This allows us to analyse changes in mobility and by contextual and socioeconomic dimensions.

Findings

Descriptive results are followed by the regression results. The main task of the descriptive section is to illustrate changes in mobility behaviour for corresponding dates in 2019, 2020, and 2021. Since we did not have access to data for October 2021 at the time of writing, we excluded October values from the descriptive graphs for presentational reasons but these were included in the regression analysis.

Descriptive Analysis

Daily mobility in Stockholm is analysed using two approaches: firstly, against the benchmark of behaviour of phones (and by implication the people carrying them) on pre-Covid days in 2019 and early 2020 and then, secondly, in terms of their residential (night-time) distance from Stockholm city centre. The descriptive analyses are designed to graph and show changes in response over time.

Figure 1 (January) and 2 (March) indicate that most people are highly localised in so-called 'normal' times before COVID (this is an all-age sample of phones) with many phones remaining within one kilometre of home. However, the effects of COVID restrictions reinforce the patterns, making people even more localised – for March 2020, January 2021 and March 2021 the proportion of the population falling into the 0-1 km band grows. There is growth of phones in this close-to-home band between January 2019 and January 2020 (Fig. 1) in non-COVID times, which could be explained as random yearly fluctuations, but January 2021 continues this trend which is more pronounced in the March 2021 data (Fig. 2). The growth in the 0-1 km band is at the expense of the proportions who move greater distances. The proportionate fall is the same across all the distance bands greater than 0-1 km.

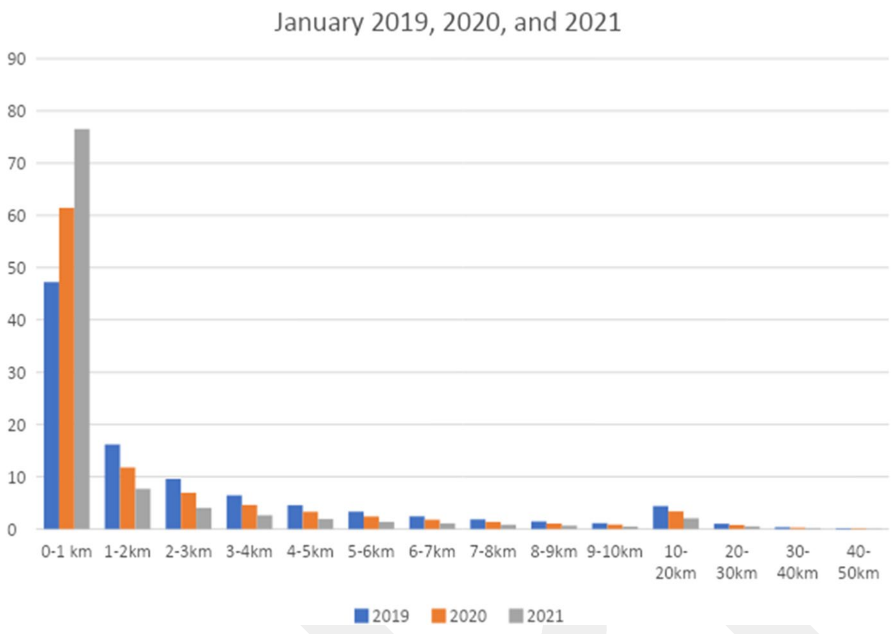

Fig. 1 Mean distances January 2019, 2020, and 2021

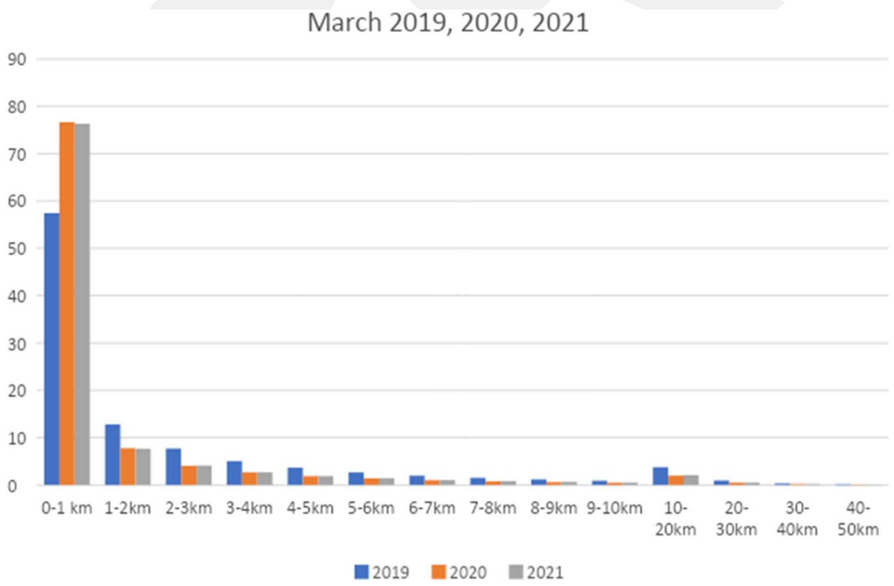

Fig. 2 Mean distances March 2019, 2020, and 2021

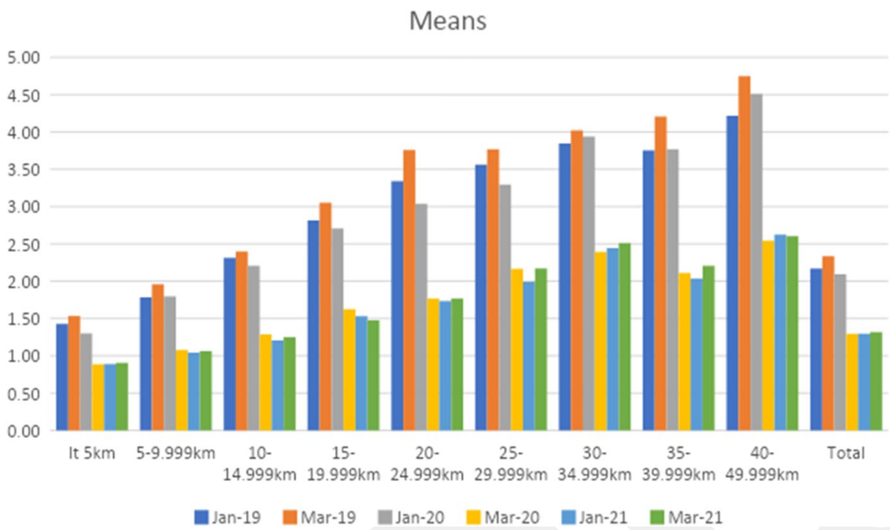

Fig. 3 Mean distance travelled by distance band from the city centre

We now consider the impact of residential distance from the centre of Stockholm. Stockholm has a monocentric structure with services and employment located in the city centre (Bamford, 2009; Söderström et al., 2015). Spatial context, and residential location relative to opportunities and services, shape geographical behaviour. People who live in job-rich urban areas usually have shorter commutes than rural dwellers, and everything else being equal, urbanites have easier access to medical, leisure, and shopping facilities than those in the suburbs. We therefore explore the pre- and during COVID-19 spatial behaviour of Stockholm residents by distance from the central railway station in 5 km bands. The variables are interest are (a) maximum distance travelled in kilometres and (b) the spatial footprint of daily activity spaces in square kilometres.

Figure 3 presents the average distances travelled by phones in January 2019, March 2019, and January 2020 (all pre-COVID) and in March 2020, January 2021, and March 2021 (during COVID). It shows the expected increase in daily distances for those residents further from the city centre. It also demonstrates that the average daily distance fell for the three COVID months in comparison with the three pre-COVID months. The distance travelled has fallen across all distance bands from the city centre and its overall effect has been to flatten the gradient of increasing distances from the city centre. It is also readily apparent that the three COVID months are very similar and much less variable than the pre-COVID months. It suggests that a large proportion of the population stayed in or very close to home but that, when the higher means are considered, those who remain mobile may still range over quite large distances.

Figure 4 reports changes in mean daily activity ellipse areas. The decrease in area matches findings shown in Fig. 3. Activity areas decreases rapidly in size for residents further away from the city centre, for groups who have experienced

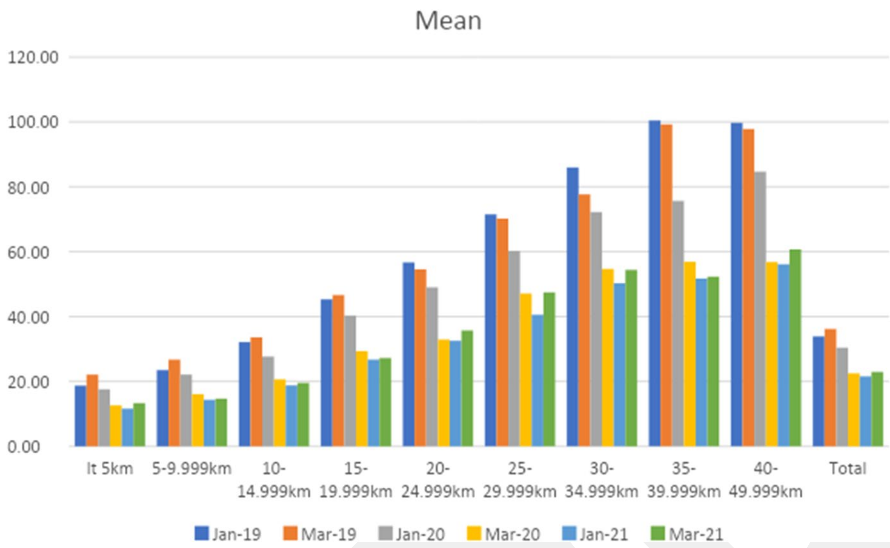

Fig. 4 Mean daily ellipse areas, expressed as km^2

greater mobility declines. City centre residents experience shrinking activity areas, but these are smaller in absolute terms simply because they were far less mobile to begin with. Overall there is also less variability in the COVID months compared to the pre-COVID months. In Appendix, graphs depicting median values (corresponding to the average values shown in Figs. 3 and 4) are available as Figs. 10 and 11. The median values are showing an even stronger over-time effect.

Regression Analysis

Table 1 shows the outputs from four models with three different dependent variables. In Model 1, the km^2 area of the activity space of each phone is used as the dependent variable. In Model 2, the radius of gyration of the mobility of each phone is employed as the dependent variable, and in Model 3 the length of the major axis of the standard deviational ellipse (as used in model 1) is used as the dependent variable. Finally, in Model 4 the area of activity space (Model 1) is run with the length of the major axis (Model 3) as an additional explanatory variable.

Regardless of dependent variable, the explanatory variables, with a few exceptions, render similar outcomes. We see that the coefficient value spans are smaller for Model 1 (the activity space models), and greater for Model 2 (radius of gyration) and especially Model 3 (major axis). This is a direct result of the value spans in each of the dependent variables. If we continue by monitoring the coefficient sizes for each row, and with the coefficient value spans in mind, we see that the same main effects can be found for three of the sociodemographic variables and for most of the date-indicators, which in turn indicates the importance of these variables in their explanatory power. If we look at specific variables, the share of risk group individuals, and highly-educated individuals among the 500 nearest neighbours from

Table 1 Table 1 shows the outputs from four models with three different dependent variables

Variables	(1) Activity space	(2) RGYRA	(3) Major axis	(4) Activity space+
Minor-major ratio				36.0913***
				(0.4713)
EventsPerPhone	0.0183***	2.8789***	6.5636***	0.0103***
	(0.0011)	(0.0422)	(0.1188)	(0.0011)
DistOJV	0.0004***	0.0083***	0.0230***	0.0004***
	(0.0000)	(0.0009)	(0.0025)	(0.0000)
Riskr500	10.4078***	723.7937***	2,137.0392***	11.6154***
	(2.4786)	(82.2779)	(228.0176)	(2.4620)
HigEdur500	6.5578***	555.2239***	1,524.4180***	6.6374***
	(1.3734)	(49.7190)	(138.4877)	(1.3670)
VMr500	-19.0221***	-787.6868***	-2,179.9275***	-18.0618***
	(1.1338)	(40.3569)	(112.2376)	(1.1264)
RGreen	1.2997***	80.0024***	220.5859***	1.3105***
	(0.0114)	(0.3992)	(1.1112)	(0.0114)
rRes	-0.5018***	-25.6802***	-73.3223***	-0.5146***
	(0.0096)	(0.3792)	(1.0556)	(0.0096)
rIndus	-0.4698***	2.4483***	4.0849	-0.4691***
	(0.0210)	(0.9261)	(2.5744)	(0.0209)
rWat	0.7841***	50.6840***	136.5552***	0.7754***
	(0.0127)	(0.4249)	(1.1790)	(0.0126)
rComm	-0.6459***	-43.1371***	-121.9026***	-0.6632***
	(0.0137)	(0.5991)	(1.6623)	(0.0137)
JobDist500	-0.0050***	-0.3386***	-0.9405***	-0.0052***
	(0.0004)	(0.0099)	(0.0275)	(0.0004)
Dist500	0.0136***	0.5944***	1.6459***	0.0137***
	(0.0006)	(0.0174)	(0.0484)	(0.0006)
Non-Covid dates				
26.Mar.19 (Ref: 17 Jan.20)	4.9831***	281.9821***	771.7426***	4.6523***
	(0.2364)	(8.8378)	(24.9700)	(0.2359)
18-Apr-19	34.5972***	1,531.5167***	4,275.5276***	34.1516***
	(0.3863)	(13.6607)	(38.6502)	(0.3864)
17-Oct-19	4.8193***	334.0668***	909.0211***	4.5472***
	(0.2456)	(9.3841)	(26.5299)	(0.2453)
16-Jan-20	1.0382***	133.8716***	352.5282***	0.9919***
	(0.2338)	(9.3859)	(26.5679)	(0.2335)
Covid dates				
26-Mar-20	-4.8708***	-598.9226***	-1,698.3074***	-5.0453***
	(0.2409)	(9.6123)	(27.2522)	(0.2410)
9-Apr-20	2.8393***	-225.6032***	-647.8799***	2.6616***
	(0.2821)	(10.9562)	(31.1402)	(0.2824)
15-Oct-20	-0.4188	-103.8975***	-321.9676***	-0.6953***

Table 1 (continued)

Variables	(1) Activity space	(2) RGYRA	(3) Major axis	(4) Activity space+
	(0.2563)	(10.1609)	(28.8078)	(0.2563)
14-Jan-21	-6.6063***	-656.4685***	-1,863.1399***	-6.4180***
	(0.2433)	(9.9311)	(28.1707)	(0.2433)
11-Mar-21	-6.2471***	-642.5592***	-1,814.5772***	-5.7407***
	(0.2454)	(10.1534)	(28.8412)	(0.2456)
1-Apr-21	14.4402***	525.9649***	1,462.3313***	14.1739***
	(0.3176)	(12.5763)	(35.7127)	(0.3179)
Constant	-4.0184***	538.0519***	1,844.8730***	-10.4141***
	(1.1476)	(40.7272)	(113.4514)	(1.1488)
Rho	0.5901	0.4965	0.4852	0.585
R^2	0.0862	0.1648	0.1641	0.0935
Observations	2,554,228	2,621,094	2,554,228	2,547,829
Number of id	614,773	621,848	614,773	613,586

Model (1), km2 area of the activity space of each phone is used as the dependent variable. In Model (2), the radius of gyration of the mobility of each phone is employed as the dependent variable. In Model (3) the length of the major axis of the standard deviational ellipse is used as the dependent variable. In Model (4) the area of activity space (Model 1) is run with the length of the major axis (Model 3) as an additional explanatory variable

Robust standard errors in parentheses

***$p<0.01$, **$p<0.05$, *$p<0.1$

each origin are associated with larger mobility areas. This is a direct result of demographic sorting in the urban region where elderly individuals (risk groups during the pandemic) are more frequently resident in non-central areas, and highly-educated individuals are more common in more affluent areas, both having more urban space per capita.

The opposite can be observed for visible minorities (VMr500), where strong negative coefficients point both to urban locations (i.e. generally shorter distances to work and services), as well as lower shares of employment (we assume that commuting accounts for a substantial share of the mobility). The coefficients for variables describing land-use for the residential context of each phone suggests that though land-use has a significant effect, it is nowhere near as impactful as other variables. The two strongest effects (Green and Water) indicate that residents in areas with greater shares of nature and water have larger/longer mobility trajectories, while the opposite is found for areas with larger shares of commercial activities (Comm) and residential areas (Res). The latter results suggest again that urban residence is associated with shorter mobility trajectories.

Finally, share of industrial activity in residential areas renders model-different and relatively weak results. In difference to amenity-rich areas (that may motivate longer commutes) industrial areas are often located in urban areas where other factors play a more important role in determining mobility distances. If we consider the distances to the nearest 500 jobs and to nearest 500 neighbours (both variable values

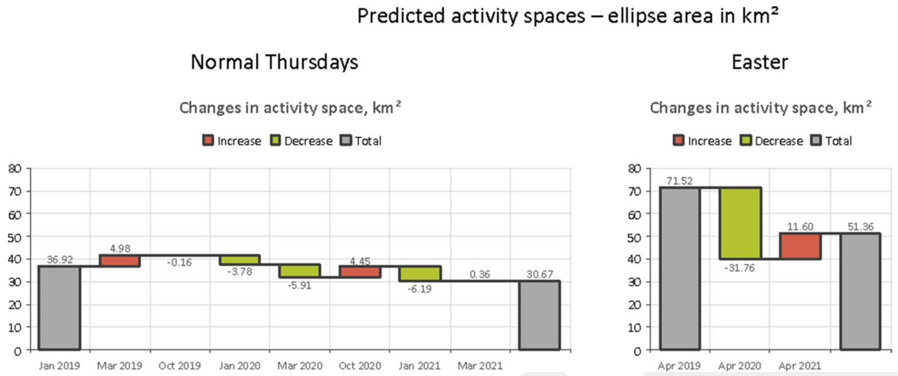

Fig. 5 Predicted activity spaces from January 2019 to March 2021

derived from PLACE), the results are opposed, as longer distances to jobs reduce mobility while greater distances to the 500-nearest neighbours increase mobility. The latter may indicate that most services (retail, education, healthcare) are common in densely-populated areas, whereas the shorter commutes in job-scarce areas may indicate larger shares of non-working populations. The date-specific effects are both strong and are overall consistent with pandemic related restrictions.

Most notable is the long-term commitment to the pandemic related mobility restrictions, where the first date after the declaration of the pandemic sees a strong reduction in mobility, and subsequent dates follow on from this. This is shown in the pandemic-unaffected Easter of 2019, which had considerably more mobility than any other date. During the first wave of the pandemic in 2020, Easter mobility was reduced to close to baseline (pre-Covid normal weekday) mobility, and the increased mobility, observed for April 2021, is still only 1/3 of the Easter 2019 mobility. It should also be noted that the majority of the adult Swedish population had been vaccinated by Easter 2021. Finally, the number of observed events per phone and date, and the metric distance to the railway station in Stockholm are all positively associated with increased mobility. The results make sense; areas further from the urban centre are less densely populated and have longer distances to services (see also Descriptive Analysis section). Since the regression results were derived from random effects (RE) regression with a panel consisting of pseudonymised phones[2], the design allows us to estimate how much of the variation (or rho) can be attributed to phone user behaviour and how much can be attributed to model-specific variables. The results indicate that between 50% and 60% of the (unexplained) variation can be attributed to the phone user's individual behaviour. The overall explanation ranges

[2] It should be noted that phone trajectory data is observed for a maximum of 24 h per phone, and in order to create a (longitudinal) panel data, aggregated data representing activity space area, radius of duration and length of major axis, are saved and used over time. This means that only relative measures of place/location (length of major axis, etc.) are used in regressions. In similar fashion, all explanatory variables are estimated for each date separately with no reference to fixed locations.

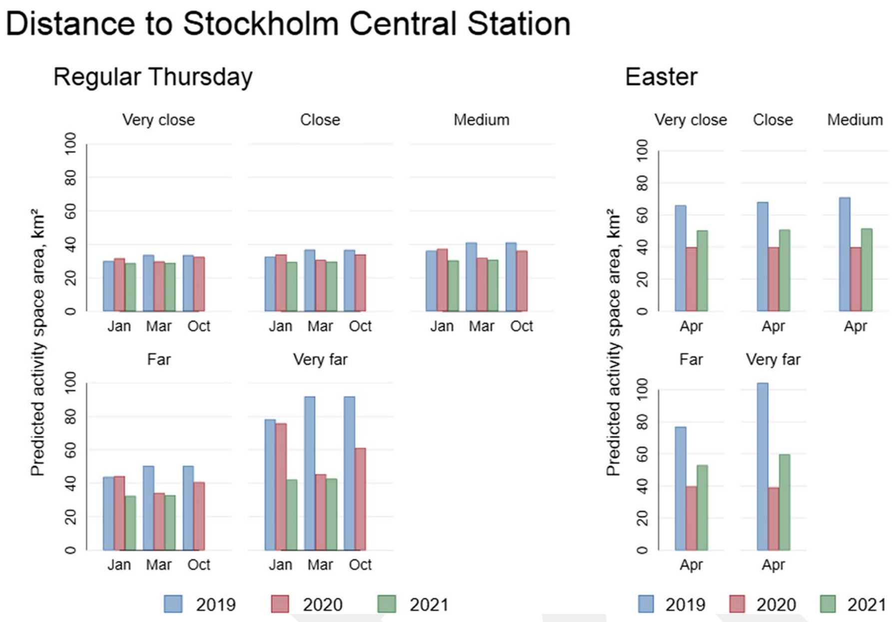

Fig. 6 Predicted activity space by distance to rail station

between 8 and 9% for the activity-space models and around 16% for the radius of gyration and major axis variables.

Figure 5 illustrates the changes in the activity spaces from 2019 to 2021 on Thursdays and Easter days. Each bar shows the change in the activity space with respect to the previous date as predicted by our model. We observe an overall decrease in mobility, which reaches its maximum in March 2020 and January 2021 when activity space decreases by up to 6 km^2 compared to pre-COVID periods. We note, however, that activity spaces increased slightly in October 2020; this also coincides with the easing of restrictions but was followed by a rapid increase in confirmed cases in Sweden. Furthermore, our model predicts more activity during Easter Holidays; however, while on average people visited places within a 71.51 km^2 activity area during Easter 2019, this decreased by almost half in the Easter Holidays of the COVID-19 period.

We also observe a heterogeneous response to policies by location and therefore varying mobility patterns among neighbourhoods located at various distances from the central station. Figure 6 shows that while centrally-located people mostly preserved their overall pre-Covid mobility behaviour during COVID, those who lived very far from Central Station limited their activity spaces substantially (by almost 60% in March 2020). People make additional trips on Easter Holidays independently of where they live.

Next, we report the mobility changes by green, water, residential and industrial fraction in land use surrounding activity spaces (Fig. 7). The results indicate that activity spaces were larger in areas with high green and water fraction both in the pre and post-COVID periods. We observe a degree of mobility substitution from

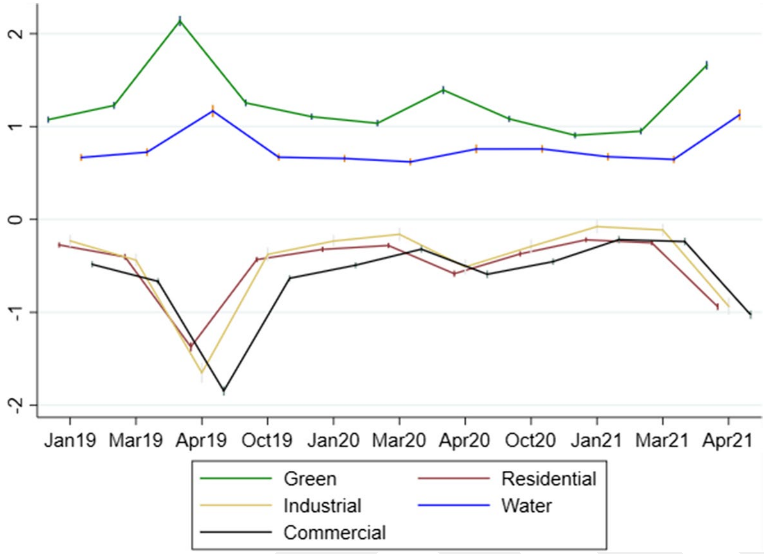

Fig. 7 The linear effect of types of land use on activity spaces

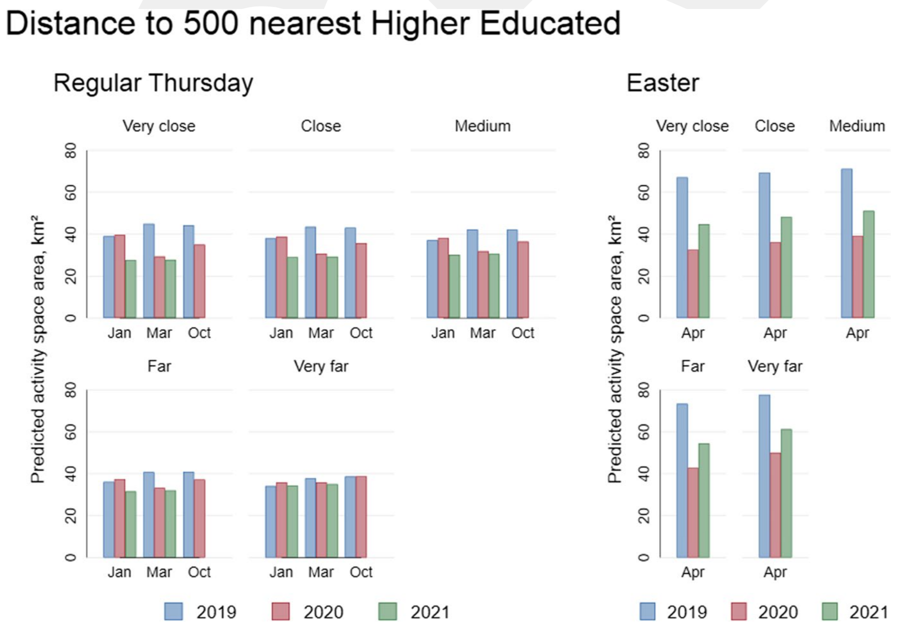

Fig. 8 Predicted activity spaces with estimated km2-ellipse area values, for phones with low to high shares (k = 500 nearest neighbours from km x km midpoint of origin) of residents classified as having a higher education

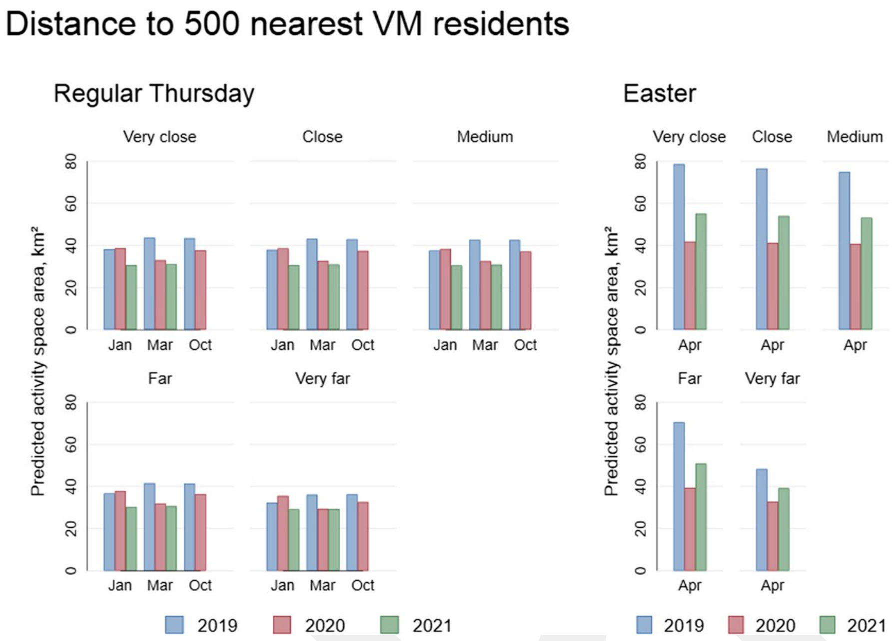

Fig. 9 Predicted activity spaces with estimated km2-ellipse area values, for phones with low to high shares (k = 500 nearest neighbours from km x km midpoint of origin) of residents classified as Visible Minorities

industrial, residential and commercial areas to natural amenities on Easter days. This seems like regular behaviour and not specific to the pandemic. However, during Easter 2020, the shift of activity spaces from urban to natural surroundings is lower than 2019.

The association between the demographic and socioeconomic composition of neighbourhoods and mobility dynamics is shown on Figs. 8 and 9. The figures demonstrate a heterogeneous response to mobility reduction by education level but not by the proportion of VMs. In the analysis, the distance to 500 nearest highly-educated people was used to represent skill concentration in neighbourhoods. Figure 8 shows that in locations with low concentrations of highly-educated population mobility levels remained at their "normal" levels. However, in areas with high concentrations of highly-educated people, mobility dropped by almost 50% in response to the first shock and remained at similar levels in 2021. On Easter days, we observe a similar reduction in mobility for all neighbourhoods characterised by various education levels. The differences between the regular Thursdays and Easter days on the basis of education concentration possibly point to an unequal access to teleworking opportunities by skill levels. While highly-educated individuals were able to work from home, in most cases low-skilled workers could not benefit from this opportunity; an opportunity that has become relevant in affecting life chances of individuals during the pandemic (by reducing the risk of exposure to Covid). Our results in Fig. 8 illustrate that compared to the baseline of Easter 2019 people could limit their mobilities by around 60% in all types of neighbourhoods, as opposed to what we observe in a low-skilled neighbourhood on a regular working day. In the Appendix two figures (Figs. 10 and 11) in which the area of activity space has been replaced with radius of gyration can be found. The results, corresponding those depicted in Figs. 8 and 9, show the same general pattern.

By using mobile phone data, Chang et al. (2021) show similar findings on mobility trajectories in the US, where disadvantaged racial and socioeconomic groups were unable to reduce their mobility and were subject to higher risk of infection. However, our study shows that vulnerability to the virus occurred on the basis of education, and potentially by class, rather than racial or ethnic identities in Sweden. As shown in Fig. 9, VM-concentrated neighbourhoods could reduce their mobilities at similar degrees to non-VM-concentrated neighbourhoods and even more so during Easter, potentially because of different religious practices.

Due to the lengthy findings section we include a bullet list summarizing our findings below:

- Mobility behavior is measured using a range of different variables including activity spaces, radius of gyration, maximum distance travelled per day and pseudonymized phone.
- The size and length of travel distances, activity spaces and radius of gyration are linked the phones' night time resting places, and the night time resting places distance to the urban core.
- Mobility is linked to the residential sorting as the elderly and highly-educated travel more because they often dwell further from the urban core while VM (Visible Minority) populations are predominantly urban.
- Relative distance to people and jobs matter. Mobility distances are relatively shorter in areas where the distance to jobs is greater (suggesting telecommuting and non-working populations are more numerous). However, in areas where distance to neighbours increases, there is a tendency to travel longer relatively.
- Mobility to areas with greater access to blue and green amenities becomes more prominent during Easter. However, during the pandemic the patterns weakened (due to restrictions).
- Sociodemographic patterns in mobility indicate that skill (education) and income but not ethnic background affected the pandemic-induced mobility behavior.

Concluding Remarks

This study studies long-term changes in spatial mobility, before and during different phases of the pandemic. It does so by asking (and answering) four questions: (1) Did the relatively liberal Swedish policy towards lockdown lead to long lasting changes in population mobility? (2) In Greater Stockholm, do we find geographical patterns of mobility change that are related to urban form, land use, and distance from the urban core? (3) Do daily spatial mobility changes reflect the socioeconomic and demographic contexts of neighbourhoods? (4) and, lastly, how far does spatial mobility vary through time? Its substantive claim to novelty is in its analysis of spatial mobility in Stockholm, subject to the liberal Swedish approach to lockdown, and a city with one of the highest levels of Covid deaths in the EU. Its methodological claim lies in its use of mobile phone data to assess mobility, its strengths lying in its wide geographical coverage and large numbers for analysis, its weakness in the lack of individual attribute data that can linked to each phone (in lieu of these data, ecological inferences had to be made through the use of the PLACE population register data). Nevertheless, similar data are being used across social science and in urban analytics (e.g., Järv et al., 2021), and the analysis shows what can be done in urban analysis at small spatial scales.

Our findings, with regard to the first question, suggest Swedish policy achieved a long-term reduction in spatial mobility in Stockholm, hence nudges and appeals personal responsibility appear to have worked. This means that people (who were able to do so) were willing to modify their spatial behaviour and to remain either at home or much nearer to home without the stick of legal enforcement. In particular, reductions in mobility cross the Hernando et al. (2020) 70% threshold of reduction of the radius of gyration, which led to falls in Covid transmission in Spain, and thus may have been epidemiologically significant although we cannot say for sure.

Answering Questions Two and Three, we also find that COVID regulations reduced interaction in the city centre, increased heterogeneity in mobility patterns and that there were clear differences in spatial behaviour before and during COVID by location – distance from the Main Railway Station – and by socioeconomic contextual variables such as higher education and income, but not by visible minority status. Spatial changes in behaviour (or their lack or lesser degree) mirror some aspects of increased mortality (e.g. greater mortality for visible minorities in Sweden who appear to have smaller observed differences from the baseline than other groups). The study also shows that socio-demographics affect mobility patterns, but a central part of the between-group sociodemographic variation is likely due to the already-existing residential geography of different groups. The elderly (classified as the at-risk group in the regression) and the higher-educated, travel further than others, while visible minorities travel shorter distances, though in the urban landscape, both the elderly and the higher educated cluster in the suburban and peri-urban parts of Stockholm, while visible minorities are concentrated in residential areas in the urban districts.

Finally, answering Question Four, there are substantial differences in mobility between dates, but the main divider is clearly the onset of the pandemic. Having said that, the Easter holidays also clearly show that festivals affect spatial behaviour; from high mobility at Easter 2019, to marginally more mobility than previous days at Easter 2020, and an increase again at Easter 2021. Easter travel behaviour (and also other Swedish Spring/Summer festivals) demonstrates how travel to areas in closer proximity to water and greenery is common at these times, and likely also used as a motivation, but also indicates the durability of seasonal behaviour – the wheel of the year turned despite Covid.

In short, this study shows that geography, both relative to the urban core, and also in access to amenities, service, and green and blue resources, plays an important role in determining spatial mobility and shaping how residents of different urban areas respond to shock events like Covid. The use of a panel regression model also showed that individual behaviour accounted for around 50–60% (model dependent) of the variance, which suggests that though there is a lot of individual variability in mobility behaviour, there is also surprisingly strong collective behaviour. The results revealed in our study underlines the importance of considering geography and land-use when modelling of human mobility behaviour and responses to events such as pandemics.

Using mobile phone data for the study of human mobility and spatiotemporal behaviour was earlier an option for only a few research in a few countries or regions. However, in recent years, these data have become more common and available for an increasing number of countries. The Mobile Tartu conference (https://mobiletartu.ut.ee/) is a major arena for biannual conferences, PhD-training, and research that uses mobile phone data and is an international node for the research community. At the time of writing the most recent added country to this network is the Republic of Serbia in which the Niš University-based Horizon consortium (UR Data), in cooperation with authors of this paper, secured access to a MIND equivalent dataset with Telekom Srbija on May 22, 2023. This means that the methods used in this paper can be extended to an increasing number of regions for similar studies via this research network.

Appendix

Figs. 10 and 11

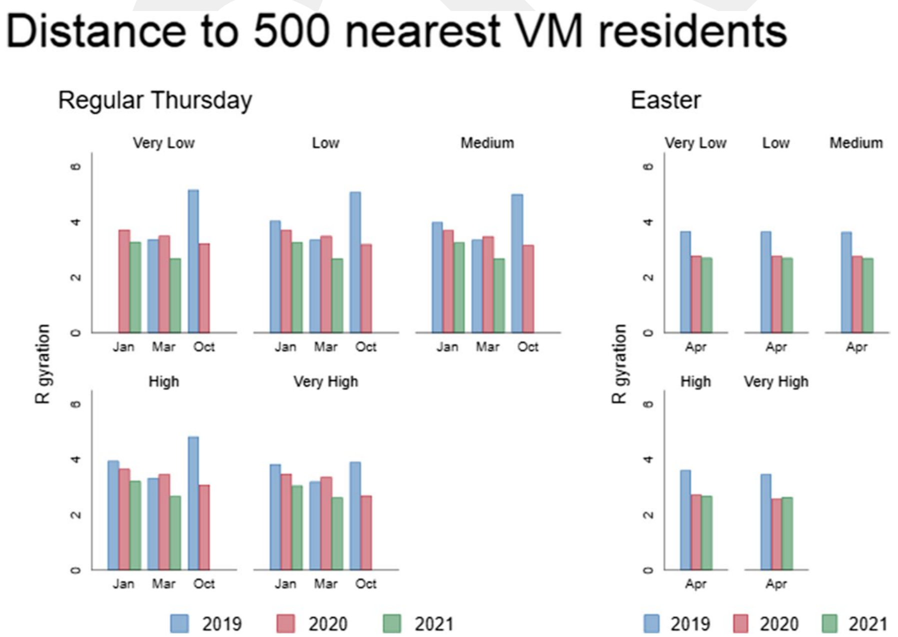

Fig. 10 Predicted radius of gyration values for phones with low to high shares (k = 500 nearest neighbours from km x km midpoint of origin) of residents classified as Visible Minorities

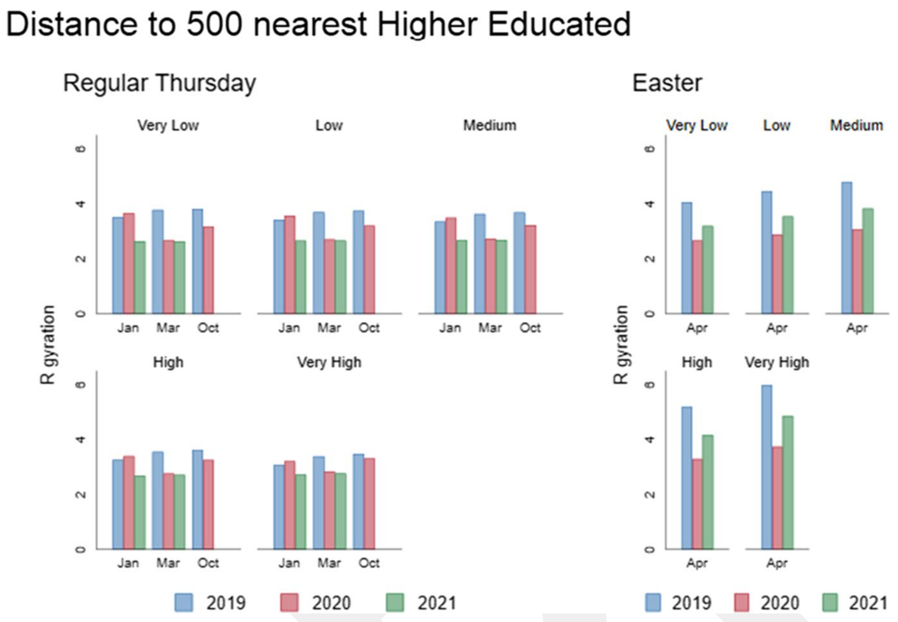

Fig. 11 Predicted radius of gyration values for phones with low to high shares (k = 500 nearest neighbours from km x km midpoint of origin) of residents classified as having higher education

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Data Availability We are legally forbidden from sharing Mobile Phone Mobility data. Swedish Population Register data is made available on the Statistics Webpage (https://www.scb.se/en/services/ordering-data-and-statistics/ordering-microdata/mona--statistics-swedens-platform-for-access-to-microdata/).

References

Andersson, S., & Aylott, N. (2020). Sweden and coronavirus: Unexceptional exceptionalism. *Social Sciences, 9*(12), 232.

Bachir, D. (2019). Estimating urban mobility with mobile network geolocation data mining (Doctoral dissertation, Université Paris-Saclay).
Bamford, G. (2009). Urban form and housing density, australian cities and european models: Copenhagen and Stockholm reconsidered. *Urban Policy and Research, 27*(4), 337–356.
Barbosa, H., Barthelemy, M., Ghoshal, G., James, C. R., Lenormand, M., Louail, T., & Tomasini, M. (2018). Human mobility: Models and applications. *Physics Reports, 734*, 1–74.
Blumenstock, J. E. (2012). Inferring patterns of internal migration from mobile phone call records: Evidence from Rwanda. *Information Technology for Development, 18*(2), 107–125.
Chang, S., Pierson, E., Koh, P. W., Gerardin, J., Redbird, B., Grusky, D., & Leskovec, J. (2021). Mobility network models of COVID-19 explain inequities and inform reopening. *Nature, 589*(7840), 82–87.
Cot, C., Cacciapaglia, G., & Sannino, F. (2021). Mining Google and Apple mobility data: Temporal anatomy for COVID-19 social distancing. *Scientific Reports, 11*(1), 1–8.
De Vries, J. J., Nijkamp, P., & Rietveld, P. (2009). Exponential or power distance-decay for commuting? An alternative specification. *Environment and Planning A, 41*(2), 461–480.
Drefahl, S., Wallace, M., Mussino, E., Aradhya, S., Kolk, M., Brandén, M., & Andersson, G. (2020). A population-based cohort study of socio-demographic risk factors for COVID-19 deaths in Sweden. *Nature Communications, 11*(1), 1–7.
Fielding, T., & Ishikawa, Y. (2021). COVID-19 and migration: A research note on the effects of COVID-19 on internal migration rates and patterns in Japan. *Population Space and Place*, *28*(6).
Gauvin, L., Bajardi, P., Pepe, E., Lake, B., Privitera, F., & Tizzoni, M. (2021). Socio-economic determinants of mobility responses during the first wave of COVID-19 in Italy: From provinces to neighbourhoods. *Journal of the Royal Society Interface, 18*(181), 20210092.
Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A. L. (2008). Understanding individual human mobility patterns. *Nature, 453*(7196), 779–782.
Granberg, M., Rönnblom, M., Padden, M., Tangnäs, J., & Öjehag, A. (2021). Debate: Covid-19 and Sweden's exceptionalism—a spotlight on the cracks in the social fabric of a mature welfare state. *Public Money & Management, 41*(3), 223–224.
Haynes, R. M. (1974). Application of exponential distance decay to human and animal activities. *Geografiska Annaler: Series B Human Geography, 56*(2), 90–104.
Hernando, A., Mateo, D., Barrios, I., & Plastino, A. (2020). Social inequalities in human mobility during the Spanish lockdown and post-lockdown in the Covid-19 pandemic of 2020. MedRxiv, 2020-10.
Hernando, A., Mateo, D., Bayer, J., & Barrios, I. (2021). Radius of gyration as predictor of covid-19 deaths trend with three-weeks offset. medRxiv, 2021-01.
Hu, L., Li, Z., & Ye, X. (2020). Delineating and modeling activity space using geotagged social media data. *Cartography and Geographic Information Science, 47*(3), 277–288.
Järv, O., Tominga, A., Müürisepp, K., & Silm, S. (2021). The impact of COVID-19 on daily lives of transnational people based on smartphone data: Estonians in Finland. *Journal of Location Based Services, 15*(3), 169–197. https://doi.org/10.1080/17489725.2021.1887526
Kang, C., Ma, X., Tong, D., & Liu, Y. (2012). Intra-urban human mobility patterns: An urban morphology perspective. *Physica A: Statistical Mechanics and its Applications, 391*(4), 1702–1717.
Lee, W. D., Qian, M., & Schwanen, T. (2021). The association between socioeconomic status and mobility reductions in the early stage of England's COVID-19 epidemic. *Health & Place, 69*, 102563. https://doi.org/10.1016/j.healthplace.2021.102563
Matekenya, D., Alegre, E., Arroyo Arroyo, X., F., & Gonzalez, M. (2021). *Using mobile data to understand urban mobility patterns in Freetown*. Sierra Leone.
Müürisepp, K., Järv, O., Sjöblom, F., Toger, M., & Östh, J. (2023). Segregation and the pandemic: The dynamics of daytime social diversity during COVID-19 in Greater Stockholm. *Applied Geography, 154*, 102926.
OECD (2020). *Capacity for remote working can affect lockdown costs differently across places*. https://www.oecd.org/coronavirus/policy-responses/capacity-for-remote-working-can-affect-lockdown-costs-differently-across-places-0e85740e/, [Online]. Last accessed June 1st 2023.
Östh, J. (2014). *Introducing the EquiPop software. Department of Social and Economic Geography*. Uppsala, Sweden.
Östh, J., & Türk, U. (2020). Integrating infrastructure and accessibility in measures of bespoke neighbourhoods. *Handbook of urban segregation*. Edward Elgar Publishing.
Östh, J., Lyhagen, J., & Reggiani, A. (2016). A new way of determining distance decay parameters in spatial interaction models with application to job accessibility analysis in Sweden. *European Journal of Transport and Infrastructure Research, 16*(2), 344–362.
Pappalardo, L., Simini, F., Rinzivillo, S., Pedreschi, D., Giannotti, F., & Barabási, A. L. (2015). Returners and explorers dichotomy in human mobility. *Nature Communications, 6*(1), 1–8.

Poot, J., Alimi, O., Cameron, M. P., & Maré, D. C. (2016). The gravity model of migration: the successful comeback of an ageing superstar in regional science. Available at SSRN 2864830.
Ravenstein, E. G. (1885). The laws of migration. *Journal of the Statistical Society of London, 48*(2), 167–235.
Shuttleworth, I., & Gould, M. (2023). Not going out during the Covid-19 pandemic? A multilevel geographical analysis of UK Google mobility reports, February 2020–December 2021. *Population Space and Place, 29*(4), e2654. https://doi.org/10.1002/psp.2654
Söderström, P., Schulman, H., & Ristimäki, M. (2015). Urban form in the Helsinki and Stockholm city regions-Development of pedestrian, public transport and car zones. Reports of the Finnish Environment Institute 16/2015. http://hdl.handle.net/10138/155224. Accessed 14 Oct 2023.
Teke-Lloyd, F. A., Türk, U., & Özgür Dönmez, R. (2022). Social mobility and pro-government mobilization: The case of July 15th pro-government mobilization in Turkey. *Southeast European and Black Sea Studies, 22*(2), 281–304.
Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography, 46*(sup1), 234–240.
Toger, M., Shuttleworth, I., & Östh, J. (2020). How average is average? Temporal patterns in human behaviour as measured by mobile phone data–or why chose Thursdays. arXiv preprint arXiv:2005.00137.
Toger, M., Kourtit, K., Nijkamp, P., & Östh, J. (2021). Mobility during the covid-19 pandemic: A data-driven time-geographic analysis of health-induced mobility changes. *Sustainability, 13*(7), 4027.
Türk, U., & Östh, J. (2019). How much does geography contribute? Measuring inequality of opportunities using a bespoke neighbourhood approach. *Journal of Geographical Systems, 21*, 295–318.
Wang, Q., & Taylor, J. E. (2014). Quantifying human mobility perturbation and resilience in Hurricane Sandy. *PLoS One, 9*(11), e112608.
Warren, G. W., Lofstedt, R., & Wardman, J. K. (2021). COVID-19: The winter lockdown strategy in five european nations. *Journal of Risk Research, 24*(3–4), 267–293.
Willberg, E., Järv, O., Väisänen, T., & Toivonen, T. (2021). Escaping from cities during the COVID-19 Crisis: Using mobile phone data to Trace mobility in Finland. *ISPRS International Journal of Geo-Information, 10*(2), 103. https://doi.org/10.3390/ijgi10020103
Xu, Y., Belyi, A., Bojic, I., & Ratti, C. (2018). *Human mobility and socioeconomic status: Analysis of Singapore and Boston* (Vol. 72, pp. 51–67). Computers, Environment and Urban Systems.

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