The long-term impact of COVID-19 on human mobility Latin America: assessing differences across population groups

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1 Introduction

Spatial human mobility is key to creating sustainable, livable and inclusive cities. At the societal level, it facilitates the transfer of knowledge, skills and labour[1], and shapes service and transport demand across urban spaces[2]. At the individual level, it enables people to access and achieve opportunities and aspirations in space[3]. Understanding spatial human mobility is thus crucial to support policy responses aimed at addressing societal challenges.

COVID-19 resulted in a notable decrease in mobility, fed by non-pharmaceutical interventions to contain the spread of COVID-19 and people's fears of contagion in crowded public spaces[4]. These reductions in mobility levels, however, did not affect everyone in the same way. For example, affluent individuals have been shown to record the greatest drops in mobility reflecting the fact that their jobs can be done fully or partly remotely[5,6]. Similarly, mobility in highly-dense urban areas recorded larger drops in mobility than in rural areas[8].

The growing body of empirical evidence has undoubtedly contributed to advancing our understanding of the impacts of the COVID-19 pandemic on mobility, however, the focus has been placed mostly on more developed countries and on the early days of the pandemic during 2020. Less is known about the longer-term patterns of resilience in urban mobility in less developed countries[8]. Particularly, urban spaces have changed considerably since then, with various configurations of hybrid or remote work still present across many sectors of the economy[9]. Thus, a quantitative assessment of the extent of these changes is important to understand the potentially unequal impacts of COVID-19 across different population groups.

Drawing on a dataset of 213 million observations from Meta-Facebook users' mobile location data, we aim to assess differences in the extent and persistence of the impact of COVID-19 on human mobility in Argentina, Chile, Colombia and Mexico. We use Meta-Facebook data to measure the volume of flows from March 2020 to May 2022 on a daily basis and at a small spatial scale (tiles of 5-10 sqkm). The evolution of mobility flows is analysed relative to a baseline period preceding the initial outbreak of COVID-19 in the spring of 2020, for areas with varying levels of population density and socioeconomic deprivation.

2 Data and methodology

We use the dataset "Facebook Movement During Crisis" provided by Meta for Good to analyse mobility patterns from March 2020 to May 2022 in Argentina, Chile, Colombia and Mexico. Meta ensures privacy and anonymity of its users by removing personal information in the data and applying privacy-preserving techniques[10]. One of these techniques is small-count dropping which consists in removing data entries where the count is lower than 10. This can result in an under-representation of population movements between areas that are sparsely populated or where the number of Facebook app users is unusually low. To counter this effect, we apply the data imputation method depicted in Figure 1. The method is adapted from[11], where a similar methodology is proposed

to impute missing data in the case of the "Facebook Population During Crisis" dataset.

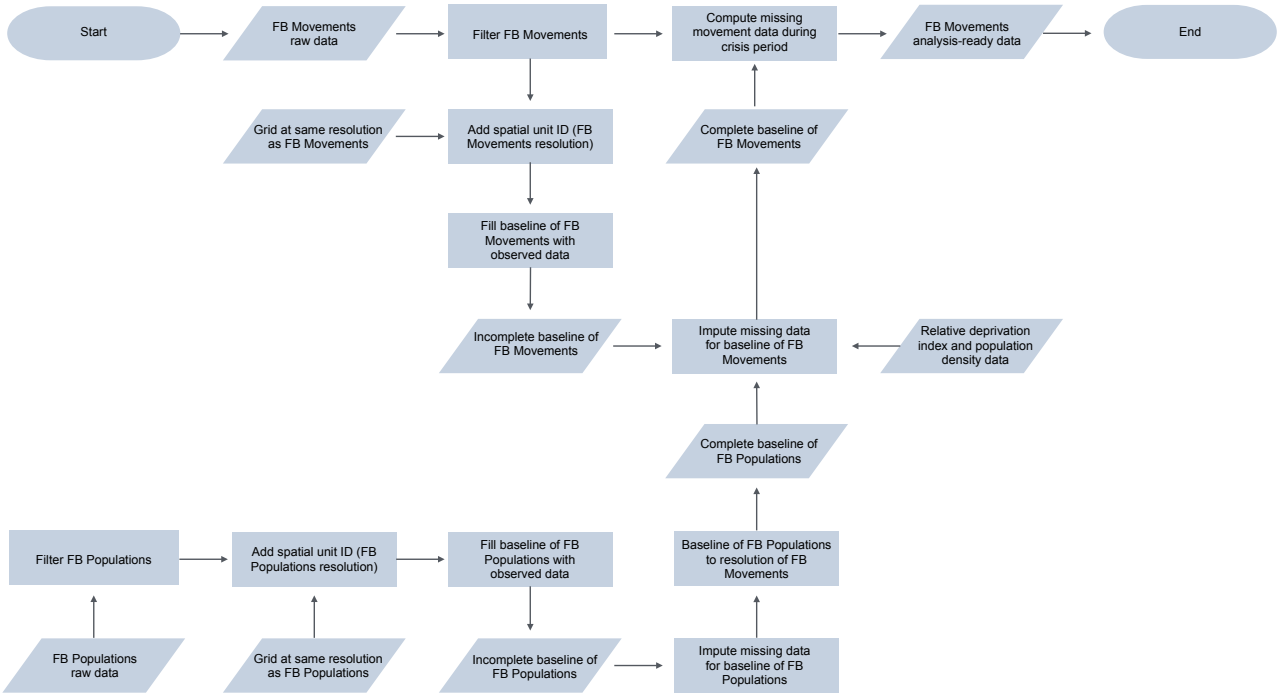

Figure 1: Methodology for "Facebook Movement During Crisis" data imputation.

As shown in Figure 1, our method requires additional data sets to estimate missing population flows. Specifically, it requires the number of Facebook app users at both origin and destination locations during the baseline period, which we obtain from the "Facebook Population During Crisis" dataset. However, this dataset also contains missing data. Following[11], we estimate missing data in the "Facebook Population During Crisis" dataset using gridded population data from Worldpop[12].

The gridded population data from Worldpop is used to classify the spatial units of analysis into categories according to their population density. In addition, we use the Global Gridded Relative Deprivation Index (GRDI) developed by NASA's Socioeconomic Data and Applications Centre to classify the spatial units into categories according to their level of socioeconomic deprivation.

3 Preliminary results

Building on existing evidence (e.g.[7]), we hypothesise that (1) levels of mobility have recovered returning to the pre-pandemic baseline levels across areas of all levels of population density; and, that (2) socioeconomic differences in mobility have endured the pandemic reflecting deep societal inequalities as knowledge-intensive businesses adopt hybrid working.

For the case of Argentina, Fig.2a shows the distribution of spatial units belonging to different population density and socioeconomic deprivation categories. While there are very few spatial units in the highest population density category, these units concentrate an important percentage of the total population of the country, as shown in Fig.2b. Fig.2c shows that in the early days of the pandemic, larger losses in inflows were recorded in the more densely populated areas and more affluent areas. Approximately two years later, mobility levels are back to baseline levels, however, the differences in mobility patterns across areas with varying levels of population density or

socioeconomic deprivation are still visible. Chile, Colombia and Mexico display analogous behaviours, although with some variations due to their individual context.

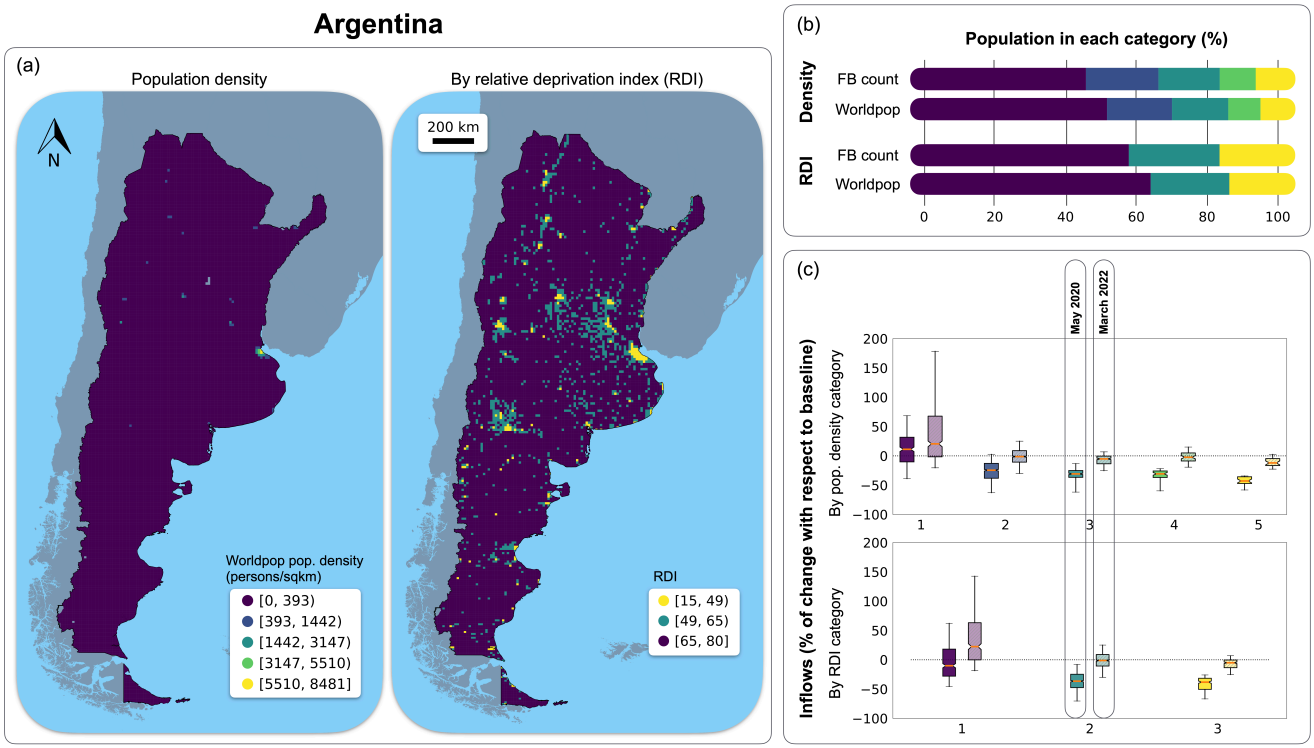

Figure 2: Argentina: (a) Classification of spatial units of analysis into population density and socioeconomic deprivation categories. (b) Share of population in each population density and socioeconomic deprivation category, according to Worldpop population data and "Facebook Population During Crisis" data during the baseline period. (c) Number of inflows to areas with varying population density and socioeconomic deprivation, relative to the pre-pandemic baseline period.

4 Discussion

A key barrier to monitor changes in human mobility patterns during and post the COVID-19 pandemic in some countries has been the lack of suitable data[8]. Traditionally census and survey data have been employed to analyse human mobility patterns[13]. Yet, these data streams are not frequently updated and suffer from slow releases, with census data for example being collected over intervals of ten years in most countries[14]. Traditional data streams thus lack the temporal granularity to analyse population movements over relatively short time periods and to offer an up-to-date representation of the urban mobility system[15]. Digital trace data (DTD), such as the data collected from Facebook app users that was used in this study, have emerged as an unique source of information to deliver this representation and capture human population movement[15]. In this work, we leverage DTD to provide quantitative evidence of the impact of COVID-19 on the evolution of human mobility across population groups.

Inclusivity is at the forefront of our analysis in two ways. First, while we consider it is worth highlighting the potential of DFD to study human movements in a timely manner, we also recognise that DTD contains biases which may compromise the statistical representatives of results. To address this, we propose a methodology to counter biases in the "Facebook Movement During Crisis" dataset that arise when removing data entries with low counts. Our methodology enables a more inclusive analysis of areas that would otherwise be overlooked in studies of human mobility. Secondly, by focusing our analysis on Latin America, we provide valuable insights into a region that remains comparatively under-studied. Latin America constitutes an ideal test-bed for evaluat-

ing our hypotheses because of its exceptionally high levels of inequalities[16] and urbanisation[17]. Half of the 20 most unequal countries in the planet are in this region, where cities in particular display some of the starkest socioeconomic inequalities[18]. Furthermore, by 2050 the share of population living in urban areas is predicted to reach 89%, with the majority concentrating in a few megacities[18]. Our analysis of human mobility in Latin America thus highlights realities that need to be addressed for the transition to more sustainable and inclusive spaces[18].

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