Urban mobility in Latin America after COVID-19

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Abstract

The COVID-19 pandemic has impacted the national systems of population movement around the world.

1 Introduction

Spatial human mobility is key to creating sustainable, liveable and inclusive cities. At the societal level, spatial mobility enables the transfer of knowledge, skills and labour to places they are needed. Spatial mobility also shapes service and transport demand across urban spaces, and enables the monitoring and control of transmissible diseases. At the individual level, mobility enables people to access and achieve opportunities and aspirations in space. Understanding spatial human mobility is thus important to supporting appropriate policy responses to address societal challenges relating to carbon emissions, urban planning, service delivery, public health, disaster management and transport.

The COVID-19 pandemic resulted in a notable reduction in mobility within cities. Nonpharmaceutical interventions to contain the spread of COVID-19 reduced overall levels of mobility. Especially during lockdowns, mobility recorded reductions in the frequency, distance and time of trips in cities across the globe. Rises in teleworking, online schooling and remote shopping activity reduced the need to travel for work, education, shopping and leisure. Coupled with fears of crowded public spaces, nonpharmaceutical interventions prompted more geographically localised mobility patterns.

However, reductions in mobility levels were highly unequal reflecting existing socioeconomic inequalities. In most countries, affluent individuals tended to record the greatest drops in mobility levels as they are predominantly employed in knowledge-intensive jobs which can be done fully or partly remotely. During the COVID-19 pandemic, the adoption of remote work reduced the need of commuting for knowledge-intensive, non-public facing jobs. At the same time, individuals from less privileged socioeconomic backgrounds displayed less pronounced declines mirroring the nature of their work requiring public-facing, face-to-face interaction, and thus a requirement for daily work commutes.

Thus, while a growing body of empirical evidence has contributed to advancing our understanding of the impacts of the COVID-19 pandemic on spatial mobility within cities, existing research has focused on more developed countries and the immediate effects of the pandemic during 2020. Less is known about the longer term patterns of resilience in urban mobility in less developed countries. Assessing the extent to which the intensity of movement has returned back to pre-pandemic levels across socioeconomic groups is important to understand the potentially unequal impacts of hybrid working in the society.

A key barrier to continuously monitor changes in geographic mobility patterns in less developed countries during and post the COVID-19 pandemic has been the lack of suitable data. Traditionally census and survey data have been employed to analyse human mobility patterns in these countries. 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. Traditional data streams thus lack the temporal granularity to analyse population movements over short-time periods and offer an up-to-date representation of the urban mobility system. Data resulting from social interactions on digital platforms have emerged as an unique source of information to deliver this representation and capture human population movement in less developed countries at scale. Particularly location data from mobile phone applications have become a prominent source to sense patterns of human mobility at higher geographical and temporal resolution in real time.

We aim to

- Context and importance of human mobility: public health , climate change

- The pandemic resulted in major changes in human mobility - unequal impacts across socioeconomic groups

- Gap 1: Little work on understanding the long-term changes in mobility - recovery

- Gap 2: little work on less developed countries - where inequalities are more pronounced

- Aim - focus on South American countries as case study.

2 Results

The evolution of the levels of movement was measured with respect to a baseline period prior to the pandemic as described in Section 4. For the purposes of the analysis, we aggregate the raw movement data temporally into months and spatially into administrative units according to various GADM levels. The analysis focuses on administrative areas that are within the boundaries of functional urban areas as specified by the Global Human Settlement Layer. For each administrative area, we compute the Relative Deprivation Index based on data from NASA's Socioeconomic Data and Applications Centre (SEDAC). Figure X displays the administrative areas included in the study, coloured according to the Relative Index of Deprivation. Predictions about the evolution of the levels of movement are made using the Prophet forecasting procedure. Further details are provided in Section 4.

2.1 The impact of COVID-19 on urban mobility

We analysed the evolution of the relative intensity of urban mobility with respect to a baseline period prior to the pandemic. Specifically, movements covering a distance of at most 70 km are considered. For a movement to be classified as urban it needs to start or end within a functional urban area from Argentina, Chile, Colombia and Mexico. The observed data is available for a two-year period starting in April 2020, just after the first wave of COVID-19 pandemic cases, and ending in March 2022. After 2022 no observations are available, however, we generate a 12-month forecast up to March 2023 in order to gain a better understanding of the recovery trends.

Figure X displays the patterns of recovery for the mobility levels in the administrative units belonging to functional urban areas in the countries of interest. The three lines in each panel represent the mean levels of mobility for administrative units grouped into one of three terciles, according to their average relative deprivation index.

Generally, there was a drop in the levels of mobility with respect to the baseline period in all four countries. This drop was especially large for Argentina, Chile and Colombia, with Mexico displaying a smaller decrease in the number of movements with respect to the baseline. Following the initial drop in movement, all four countries evolve towards the recovery of baseline levels of urban mobility, with a generally increasing trend. There are fluctuations from the general trend, which manifest differently for each country. These fluctuations mirror each other in the case of Argentina and Colombia, where urban mobility sharply bounces back closer to pre-pandemic levels around July of 2020. Chile and Mexico display more progressive patterns of recovery, although Chile never reaches baseline levels. These fluctuations are unique to each country and can be attributed to local factors such as the effects of seasonality or the different stringency measures imposed by the national governments during the pandemic.

From Figure X, we observe that there is a consistent tendency in how administrative units with varying levels of deprivation were affected by the pandemic. For all four countries, we observe that the administrative units in the most deprived tercile are the ones that experienced the smallest loss in levels of mobility at the beginning of the pandemic. Differences in the levels of mobility across relative deprivation terciles diminish with time. Argentina and Chile stand out as the countries with the largest differences in mobility levels for different relative deprivation terciles.

2.2 Socioeconomic deprivation and recovery of urban mobility

In this section we explore further the role of socioeconomic deprivation in the evolution of the levels of urban mobility. For a given point in time (i.e. a month), we start by considering the relationship between the number of movements relative to the pre-pandemic baseline period and the average relative deprivation index, at the administrative unit level. We assume that this relationship is linear and we use a linear regression to estimate the slope and intercept characterising the line of best fit. This is shown for April 2020 and March 2022 in the right-hand side panels of Figure X. After obtaining the slope and intercept for every month, we are able to plot the evolution of these parameters for both the observed and forecasted data, as displayed on the left-hand-side panels of the same Figure.

We find patterns in the evolution of the estimated parameters that characterise the relationship between the levels of urban mobility and RDI. In Argentina, Colombia and Mexico, we observe that the slope of this relationship evolves to become smaller over time. The tendency is not apparent in Chile, where the slope of the relationship remains approximately the same despite the temporary fluctuations. The slope captures the extent of differences in the level of urban mobility across administrative units with varying levels of socioeconomic deprivation. It can therefore be regarded as a measure of inequality. A slope equal to zero would mean that all administrative units display the same intensity of movement regardless of their socioeconomic deprivation levels. Given the patterns observed in Argentina, Colombia and Mexico, we find that at the beginning of the pandemic there were notable inequalities between socioeconomic groups in terms of the levels of urban mobility. While it has taken more than two years for Argentina and Mexico to close the gap (their slope is close to zero from spring 2022), inequalities persist in Chile and Colombia as of March 2023.

The intercept of the relationship displays stronger patterns, which are consistent across the four countries. The intercept captures the urban mobility levels in administrative where relative deprivation is zero, or in other words, if there was no socioeconomic deprivation in an administrative area, the intercept would represent its level of mobility. The intercept was well below the baseline level at the early stages of the pandemic. As observed in Figure X, while there are some differences between countries in the evolution of the intercept, the general tendency is for the intercept to increase. While Argentina and Mexico reach values that are closer to the baseline towards the end of the forecast period, the intercept for Chile and Colombia remains lower. Therefore, if there were areas with no socioeconomic deprivation, we would have seen a recovery in the levels of mobility, although not quite back to baseline levels in the case of Chile and Colombia.

3 Discussion

4 Methods

4.1 Meta-Facebook movement data

To capture population movements, we used anonymised aggregate mobile phone location data from Meta users for Argentina, Colombia, Chile and Mexico, covering a 24-month period from April 2020 to March 2022. We used the dataset Facebook Movements created by Meta and accessed through their Data for Good Initiative (https://dataforgood.facebook.com). The data are built from Facebook app users who have the location services setting turned on on their smartphone. Prior to releasing the datasets, Meta ensures privacy and anonymity by removing personal information and applying privacy-preserving techniques (Maas et al. 2019). Small-count dropping is one of these techniques. A data entry is removed if the population or movement count for an area is lower than 10. The removal of small counts may mean that population counts in small sparsely populated areas are not captured. A second technique consists in adding a small undisclosed amount of random noise to ensure that it is not possible to ascertain precise, true counts for sparsely populated locations. Third, spatial smoothing using inverse distance-weighted averaging is also applied is applied to produce a smooth population count surface. The Facebook Movements dataset offers information on the total number of Facebook users moving between and within spatial units in the form of origin-destination matrices. The data is temporally aggregated into three daily 8-hour time windows (i.e. 00:00-08:00, 08:00-16:00 and 16:00-00:00). The dataset includes a baseline capturing the number of movements before COVID-19 based on a 45-day period ending on March 10th 2020. The baseline is computed using an average for the same time of the day and day of the week in the period preceding March 10th. For instance, the baseline for Monday 00:00-08:00 time window is obtained by averaging over data collected on Mondays from 00:00 to 8:00 for the 45-day period. Details about the baseline can be found in Maas et al. (2019). The Bing Maps Tile System developed by Microsoft (Microsoft) is used a spatial framework to organise the data. The Tile System is a geospatial indexing system that partitions the world into tile cells in a hierarchical way, comprising 23 different levels of detail (Microsoft). At the lowest level of detail (Level 1), the world is divided into four tiles with a coarse spatial resolution. At each successive level, the resolution increases by a factor of two. The data that we used are spatially aggregated into Bing tile levels 13. That is about 4.9 x 4.9km at the Equator (Maas et al. 2019).

4.2 Spatiotemporal data aggregation

Since the focus of this work is on urban mobility, we focus the analysis on Functional Urban Areas (FUAs), defined by the Global Human Settlement Layer. The spatial extent of the FUAs is often large and may include several towns and neighbourhoods displaying a variety of socioeconomic characteristics, hence using FUAs as the spatial units of aggregation would considerably mask the heterogeneity in the mobility patterns. While the original unit of aggregation for the movement data, i.e. the tiles from the Bing Maps Tile System, offers the highest degree of spatial granularity available, the interpretation of findings from an analysis based on administrative units is often more valuable. For this reason, we perform a spatial join to aggregate the movement data into administrative units at the GADM level 2 or 3. Only flows of people starting or ending within the boundaries of a FUA are considered.

While the original movement data is originally aggregated into 8-hour windows, this resolution is too fine for our analysis. Since the analysis is focused on the longer-term evolution of patterns of urban mobility, we aggregate the movement data by month.

In our analysis, we use the Relative Deprivation Index (RDI) as a measure of socioeocnomic deprivation. The RDI data is made available via NASA's Socioeconomic Data and Applications Centre (SEDAC), with a spatial resolution of 1km pixels. We perform a spatial join of the gridded data and the administrative units and compute the average RDI within each of these units.

4.3 Time series analysis

For the countries included in the analysis, the movement data is available until March 2022. In order to gain a better understanding of the recovery trends after the pandemic, we generate a 12-month forecast up to March 2023. This is done using Prophet, a procedure to forecast time series data based on an additive model where non-linear trends can be fit with seasonality effects, holiday effects and other external factors such as the stringency index. For the analysis, only seasonality effects are included as they yield the most realistic predictions.

In Figures X and Y, outliers are removed. Outliers are defined as administrative units which, at any given month, have a z-score greater than 4 for the relative intensity of movement. Furthermore, a Savitzky-Golay filter is applied to smooth the time series data, using a length of 4 units for the filter window and order 2 polynomials to fit the samples.

5 References