The mid-term impact of COVID-19 on human mobility patterns in Latin American countries*

Carmen Cabrera-Arnau [†1], Miguel González-Leonardo[2], Andrea Nasuto[1], Ruth Neville[1], and Francisco Rowe[1]

[1]Geographic Data Science Lab, Department of Geography and Planning, University of Liverpool, Liverpool, United Kingdom

[2]Center for Demographic, Urban and Environmental Studies, El Colegio de México (COLMEX), Mexico City, Mexico

Abstract

Recent empirical studies, predominantly from countries in the Global North, have shown that the COVID-19 pandemic disrupted human mobility at different spatial scales, but particularly in big cities, initially identified as epicentres of infections. Lockdowns, remote work, and online education decreased the demand for commuting and urban living, resulting in an "urban exodus". Despite the existing evidence, little is known about whether counterurbanisation movements have unfolded similarly in the Global South. In this study, we use anonymised, high-resolution location data from Facebook users to answer the following research questions: i) to what extent are people leaving cities? ii) are there variations across countries? iii) are there changes in mobility patterns over time? iv) how long do these changes last? The methodology involves three steps. Firstly, we quantify the number of movements between different locations in each country. Second, we use statistical modelling and spatial interaction models to assess the strength of the flows between specific origin-destination pairs at different points in time. Thirdly, for each country, we use cluster analysis to characterise different mobility behaviours according to the population density at the origin and the destination. We obtain population density data from Worldpop at a resolution of 1 sqkm, and we use it as a proxy of the level of urbanisation at these locations.

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†*Corresponding author*: c.cabrera-arnau@liverpool.ac.uk

1. Introduction

The COVID-19 pandemic globally resulted in disruptive shocks to the human mobility system. Governments stringency measures and the economic downturn caused by the pandemic constrained international migration (**internat2021?**; **gonzález-leonardo2022?**; **gonzález-leonardo2023?**) and population movements within countries (**nouvellet2021?**; **gonzález-leonardo2022a?**; Wang et al. 2022; **rowe2023?**). During early stages of the pandemic, big cities became the main epicentres of COVID-19 infections and deaths (**Pomeroy2021?**) due to their higher connectivity via air travel, higher population density and concentration of public-facing jobs (**brandén2020?**; **bhadra2020?**). As a result, governments implemented non-pharmaceutical interventions, such as lockdowns and business closures, leading to increases in unemployment and removing the urban vibrancy (**blustein2020?**; **BBCnews2023?**). In addition, remote work and online teaching reduced the need for commuting, living close to work and education centers, and added pressure for individuals living in small and crowded spaces to move out of cities and look for more affordable and comfortable housing (**nathan2020?**; **USBureauLabor2021?**). These changes are believed to have reduced the attractiveness of cities during the pandemic, while suburbs and rural areas have gained popularity (**florida2021?**). As a result, a number of headlines have claimed the emergence of an 'urban exodus' to areas with lower population densities (e.g. (**TheGuardian2020?**)).

Despite their potential rise in popularity, remote locations offer limited availability and diversity of job opportunities, and tend to lack infrastructure and services, such as schooling and health, to effectively accommodate a large population influx (**Pinilla2021?**; **oecdreg?**). They generally lack high-speed Internet connection which is vital for teleworking (**Chen2004?**). Additionally, most jobs cannot be done remotely (**oecdsoc?**), and some companies have returned to in-person office work or have implemented hybrid forms of work, following the relaxation of stringency measures (**McKinsey21?**). Schools and universities have also returned to face-to-face teaching. Therefore, living close to work or study places remains relevant. Businesses and leisure activities in cities have gradually returned to normal, reinvigorating the economic functioning and urban life. Collectively, these arguments suggest that a potential increase in counterurbanisation movements during the pandemic was concentrated during periods of stringency measures and is likely to be short term. Big cities have successfully weathered previous pandemics (**huremovic2019?**; **Glaeser20?**) and are likely to remain attractive places to live. Thanks to agglomeration economies, cities are normally regarded as centres for economic growth, clusters of talent, consumer bases and spaces for face-to-face interaction and diversity (**storper2004?**; **florida2021?**).

Recent empirical evidence has shown a decline on human mobility during periods of severe stringency measures, coupled with a rise of movements from cities to less populated areas and a slowdown of urbanisation movements across some countries of the Global North: the United States (**ramani2021?**), United Kingdom (**rowe2023?**; Wang et al. 2022), Spain (**gonzález-leonardo2022b?**; **gonzález-leonardo2022a?**), Germany [@; (**stawarz2022?**)], Sweden (**vogiazides2022?**), Norway (**tønnessen2021?**), Australia (**perales2022?**) and Japan (**kotsubo2022?**). The majority of movements away from cities headed to their suburbs (**vogiazides2022?**; **stawarz2022?**) or rural areas in their close proximity (**gonzález-leonardo2022b?**; **gonzález-leonardo2022a?**) showing in some instances a "doghnut effect", with a decline in population movements directed to cities and a rise in the inflow of people to less dense surrounding areas (**ramani2021?**). Studies demonstrated that professionals (**tønnessen2021?**) and individuals with a high income (**haslag2021?**), those who are potentially able to practice remote working, underpinned movements away from large cities. In addition, research has shown that a large share of counterurbanisation movements is headed to touristic locations with a high concentration of second homes, suggesting that middle and high class individuals may have been key actors in movements from cities to less populated areas during the pandemic (**gonzález-leonardo2022a?**). However, most studies suggested that variations in internal population movements during the pandemic are likely to be temporary and have not altered previous macro-structures of human mobility across the rural-urban hierarchy (**rowe2023?**).

In Latin America and the Caribbean, a reduction in internal population movements was documented during periods of high stringency (**aromí2023?**), but there is no evidence on how human mobility has changed across the rural-urban continuum. Anecdotal reports have shown that movements away from cities seem to have accelerated in two countries of the Global South, India (**irudayarajan2020?**) and South Africa (**ginsburg2022?**), while urbanisation trends have decelerated. However, lack of suitable up-to-date data has prevented us from properly assessing the "urban exodus" hypothesis in Global South countries, as well as the extent, spatial patterns, and durability of potential changes on internal population movements. The evidence for these two countries suggested that increasing counterurbanisation movements during the pandemic in India and South Africa could be underpinned by internal migrants residing in cities who returned to their hometowns due to a rise in unemployment (**irudayarajan2020?**; **ginsburg2022?**). However, recent studies have shown that urban residents from wealthy neighborhoods were more likely to move to rural areas than those from low income neighborhoods during the first wave of the pandemic in Brazil, Colombia, Mexico, Indonesia, Philippines and South Africa (**lucchini2023?**).

It is known that human mobility within countries tends to vary in systematic ways with development levels (**bell2015?**). In Latin America and the Caribbean, 28.6% of the population was living on less than $6.8 per day in 2020 (**WorldBank2023?**) and the informality rate was about 53% in 2016 (**OIT2018?**). Thus, we could expect different pandemic impacts on the patterns of internal population movements between countries in the Global North and the Global South. The way in which COVID-19 unfolded in each country, with varying levels of stringency measures, may have also produced different outcomes on human mobility.

Traditionally, censuses have been used to analyse human mobility patterns within Global South countries, which lack register data (**bell2015?**; **bernard2017?**). Censuses, however, are normally updated every 10 years, lacking the temporal granularity to explore population movements over yearly, monthly or short-time intervals.

Digital traces data from mobile phone applications, on the other hand, provide a unique opportunity to capture internal population movements with small spatial and temporal granularity in multiple countries (**green2021?**; **rowe2021?**). Drawing on geographically granular Meta-Facebook data from March 2020 to March 2022, we aim to analyse how the pandemic has changed the patterns of human mobility across the rural-urban hierarchy in four Latin American countries: Argentina, Chile, Colombia and Mexico. We aim to address the following research questions: 1) To what extent did people leave cities and move to less populated areas in these countries? 2) Which are the spatial patterns of potential changes on internal population movements? 3) How have the patterns of human mobility changed over the course of the pandemic? 4) Are potential changes likely to endure the pandemic?

The rest of the paper is structured as follows: …

2. Background

2.1. What do we know about internal population movements during the pandemic?

The COVID-19 pandemic led to an overall decline in human mobility within countries (**nouvellet2021?**). Research has shown that internal population movements across the rural-urban continuum decreased in the United States (**ramani2021?**), several European countries, Japan and Austria during 2020 (**rowe2023?**). Declines ranged from 2.5% in Spain to 8.5% in Australia. The largest drops occurred during periods of national lockdowns and the implementation of other stringency measures, such as mobility restrictions, work and school closing, while levels of internal population movements recovered or exceeded pre-pandemic figures when lockdowns were lifted. Declines were partially attributed to a reduction in involuntary migration during lockdowns, a loss of labour market dynamism due to the pandemic, fewer people changing jobs and increasing remote work (**perales2022?**).

COVID-19 has also altered patterns of internal population movements across the rural-urban hierarchy (Rowe et al. 2022). In large metro areas across the United States, population movements, as well as households and businesses, shifted from central cities to suburbs and exurbs during 2020 (**ramani2021?**). These authors label this trend as a "doughnut effect", reflecting a decrease in population inflows and activities in city centers and a growth in suburban rings. They found a sizeable "doghnut effect" in large cities, a smaller effect in medium-sized cities and almost no effect for small cities. A similar trend was observed in Norway (**tønnessen2021?**), Germany (**stawarz2022?**), Sweden (**vogiazides2022?**) and Japan (**fielding2021?**; **kotsubo2022?**), where net migration rates in big cities declined, while population movement to their suburbs increased. In addition, this trend was accompanied by a deceleration of urbanisation trends and unusual population gains in rural areas due to an acceleration in counterurbanisation movements, mostly in rural locations which are known to be holiday destinations with a high concentration of second homes and are generally located in the close proximity to big cities. An increase of counterurbanisation was the main pandemic outcome on human mobility in Spain (**gonzález-leonardo2022b?**; **gonzález-leonardo2022a?**), the United Kingdom (Wang et al. 2022; Rowe et al. 2022) and Australia (**perales2022?**), where there is no evidence of a "doghnut effect", since substantial variations in suburbs were not found across these countries.

However, studies suggest that variations are likely to be temporary (**rowe2023?**). In Spain, the urbanisation movement returned to pre-pandemic levels when the lockdown ended in mid-June 2020 (**gonzález-leonardo2022b?**) and unusually high levels of counterurbanisation persisted over 2021, although the majority of movements continued to occur between and within urban areas (**gonzález-leonardo2022a?**). In Australia, the pandemic has caused minor changes in spatial patterns of internal migration, and its effects were minimal by the end of 2020 (**perales2022?**). In the United Kingdom, mobility patterns returned to those registered prior to the pandemic after the easing of non-pharmaceutical interventions (Rowe et al. 2022; Wang et al. 2022). These findings suggest that COVID-19 generated shock waves leading to temporary changes in the patterns of internal population movement across the rural-urban continuum, but it has not significantly altered the prevalent macro-structures of population movement within countries.

Despite some evidence in the Global North, lees is known about the impact of COVID-19 on human mobility in the Global South countries. In Latin America and the Caribbean, internal population movements declined by 10% during periods of severe stringent measures, from 16-19% in Bolivia, Ecuador and Argentina to less than 3% in Paraguay and Venezuela (**aromí2023?**). However, there is no evidence about pandemic outcomes on human mobility across the rural-urban continuum. To date, surveys carried out in India (**irudayarajan2020?**) and South Africa (**ginsburg2022?**) have shown anecdotal evidence suggesting that urbanisation trends declined during the pandemic, while movements from cities to rural areas increased. Both studies pointed out that a number of rural residents initiating a migration decreased during 2020 and some labourers in major cities seem to have returned to their hometowns due to job losses, since stringency measures have extensively impacted the functioning of the economy (**ghosh2020?**). Many internal migrants residing in Indian cities lost their jobs and were unable to afford basic necessities (**ILO2020?**). Collectively, these findings suggest that vulnerable populations seem to have played a role in increasing counterurbanisation movements in Global South countries. However, recent work has shown that high-wealth groups residing in cities across Mexico, Colombia, Brazil, Indonesia, Philippines and South Africa were on average 159% more likely to have moved to rural area compared to those of low-wealth groups during early stages of the pandemic (**lucchini2023?**), in line with the evidencee found for Global North countries.

Despite anecdotal evidence suggesting pandemic impacts on the patterns of human mobility across the rural-urban hierarchy in the Global South, lack of suitable data has not allowed us to identify and quantify the magnitude of these impacts. In this paper, we use Meta-Facebook data to provide evidence on the effect of the pandemic on the patterns of internal population movements across four Latin American countries.

2.2. Contemporary trends of human mobility across the rural-urban hierarchy in Latin America

Until 1980, rural to urban migration dominated internal population movements in Latin America with significant levels of population redistribution, especially during the rapid industrialisation process between the 1950s and 1970s when a critical mass of individuals moved from villages and towns to urban areas (**firebaugh1979?**; **lattes95?**; **sobrino12?**). Urban growth due to internal mobility was primarily concentrated in large urban centres resulting in a significant population imbalance between the chief cities and other settlements (**PintoDaCunha02?**; **lattes2017?**). As a consequence, Latin America shows high rates of urbanisation with more than 81% of the population living in cities, the highest figure after North America, and about 46% of urban residents settled in cities with more than 1 million inhabitants (**UNpopulation19?**).

Currently, internal population movements amongst cities dominate the migratory system in Latin America, while rural to urban flows are of less importance (**bernard2017?**; **rodríguez-vignoli2018?**; **UNpopulation19?**). According to the 2010 census round, 80% of internal migrants moved between cities (**rodríguez-vignoli2018?**). Contrary to the period preceding the 1980s, medium-sizes cities (those between 500K and 1 million inhabitants) experienced the highest net migration rates, while large cities (>1 million) presented balanced rates and small cities (>500K) lost individuals by internal population movements (**rodríguez-vignoli2018?**). Changing patterns in human mobility within Latin American countries were driven by a decline in internal migration since the 1980s crisis (**chávezgalindo2016?**) and deconcentration dynamics in large urban centres, such as Mexico City (**sobrino2006?**) or Santiago de Chile (**gonzálezollino2006?**), where long distance inflows have declined over time. At the same time, there has been an increasing domestic and foreign investment in export-oriented activities or tourism industries in certain middle-sized cities, fostering the geographic dispersal of employment opportunities and increasing the attractiveness of these cities (**Brea03?**; **Pérez-Campuzano13?**; **chávezgalindo2016?**).

Suburbanisation also represents an important type of internal population movement and has increased over time due to the growing expansion of Latin American cities (**graizbord2007?**; **chávezgalindo2016?**). These movements are underpinned by flows of middle- and upper-class families moving away from central cities to surrounding auto-segregated areas of wealthy individuals (**borsdorf2003?**; **rodríguezvignoli2017?**). Low-income populations also settle in specific areas within suburbs where the cost of living is usually cheaper than in cities (**janoschka2002?**; **rodríguezvignoli2017?**). A large proportion of both wealthy individuals and low-income residents commute daily to central cities, mainly for work reasons (**chávezgalindo2016?**). Recently, reurbanisation dynamics have also been observed due to gentrification processes in specific central areas (**sobrino12?**; **chávezgalindo2016?**). In this paper, we analyse how the COVID-19 pandemic has changed patterns of internal population movements across the rural-urban hierarchy in Mexico, Colombia, Perú, Chile and Argentina.

3. Data

The analysis proposed in this paper is based on several data sets. Firstly, Facebook Population and Facebook Movements are data sets based on the Facebook users' location history. The data sets were created by Facebook's owner company Meta and can be accessed through their Data for Good programme (`https://dataforgood.facebook.com/`). Prior to releasing the data sets, Meta applies three techniques to ensure privacy and anonymisation. First, a small undisclosed amount of random noise is added to ensure that precise location cannot be identified for small population counts in sparsely populated areas. While removing small counts may lead to an underrepresentation of the population in these places, the geographic distribution of population is still reflected in the data. Second, spatial smoothing is applied to produce a smooth population count surface using inverse distance-weighted averaging. Third, any remaining population counts of less than 10 are removed from the final data set (see Maas et al. Maas et al. (2019) for details).

Both data sets Facebook Population and Facebook Movements contain data corresponding to a time period comprising approximately two years, starting from March 2020, and to four Latin American countries, Argentina, Chile, Colombia and Mexico. The data in both data sets is temporally aggregated into three 8-hour windows (00:00–08:00, 08:00–16:00 and 16:00–00:00) for every day in the aforementioned two-year period. It is spatially aggregated into tiles according to the Bing Maps Tile System. This geospatial indexing system was developed by Microsoft and it partitions the world into square cells at various levels of resolution. The Facebook Movements and Facebook Population datasets are aggregated into various levels of resolution depending on the country, and the length of the Bing tile sides vary also by country according to the country's distance to the Equator, even when two countries use tiles at the same level of resolution.

The Facebook Population data set provides information on the number of active Facebook users in each tile. The data set Facebook Movements captures the total number of Facebook users moving between pairs of origin and destination Bing tiles. We note here that due to the nature of the Facebook Movement data, we cannot distinguish between different types of movements, for example, daily commutes to work or permanent changes of address. However, we are still able to detect the evolution of movements between origin-destination pairs of Bing tiles and hence, we are able to capture the impact that COVID-19 has on mobility patterns.

On top of the data for the two-year period, each entry in the Facebook Population and Facebook Movements datasets include data for baseline levels before COVID-19. The baseline values are computed based on a 45-day period ending on the 10th of March of 2020. The data sets also include a 'quality' score indicating the number of standard deviations by which the observed data at specific locations and time windows differ from the baseline values, hence highlighting statistically significant changes.

An additional data set from WorldPop was used to capture the spatial distribution of population density in the different countries analysed here. The WorlPop dataset is in raster format and contains gridded population data at 1 sqkm resolution.

4. Method

4.1. Data pre-processing

Ultimately, we work with a dataset where each entry represents a population flow between an origin and a destination pair. For each entry, we consider when the movement took place, the population density at the origin and destination, the number of active Facebook users at the origin and destination and?

4.1.1 Spatial aggregation

The working dataset is aggregated at the same level as the Bing tiles used to track the movements in a given country. To each Bing tile, we aggregate WorldPop population data and use it to estimate the population density of each Bing tile.

4.1.2 Temporal aggregation

The raw data is aggregated into 8-hour windows for every day in the two-year period. However, we are interested in longer-term trends and not in how population flows vary throughout the day. For this reason, we obtain estimates for the parameters in the models described in subsection **??** by splitting the total data set by month. For the visualisations in section 5, we also present the data aggregated by month.

4.2. Classifying Bing tiles according to their population density

Here we aim to understand how the population density at the origin and the destination might influence mobility behaviours. To help characterise the population density between orign and destination, we classify the Bing tiles into 10 discrete categories of population density according to the Jenks natural breaks classification method, hence obtaining a categorisation of Bing tiles a lot more detailed than the traditional binary rural/urban classification.

4.3. Estimating the strength of the flows between tiles of different population density categories

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In this section, we propose a statistical model to capture the extent to which the strength of the population flows is systematically impacted by the density classes of the origin and destination tiles, and how this effect varies over time. Our approach here is very similar to that proposed by (**?**).

images/Map_density_histogram.png

Figure 1. Maps of population density categories by country with histograms, showing that the distribution of Bing tiles in each density category.

While we could obtain the population flows between different population classes and their evolution over time, the results would fail to capture specifically the effect of the density classes of the origin and destination tiles. This is due to the fact that movement patterns are influenced not only by the population density of the starting and ending locations, but also by factors such as the distance, the population size, the time of the week and day at which movements take place, etc. These additional variables can act as confounding factors, obscuring the actual impact of population density. In order to disentangle and obtain a more accurate estimation of the importance of population density, we chose to utilise a regression modeling approach. I AM HERE

We adopted a spatial interaction framework (Rowe, Lovelace, et al., 2022). We used population flows between tiles by time window and day (as described in Section 3), and modelled them as a function of characteristics of the flow itself (Fij), the origin (Tilei) and destination (Tilej) tiles and the temporal nature of the flow (Tw). Crucially, we included indicator variables that capture the pair of population classes (Figure 1) of the origin and destination tile. In mathematical form:

(2) where μijw is the expectation of the flow of people from tile i to tile j in the time window w; is an intercept; is a series of indicator variables that reflect the pair of population density classes of a given origin i (I) and destination tile j (J), resulting in 99 pairs (10 classes×10 classes minus one so it is not collinear with); dij is the geographic distance between tiles i and j; qijw is a measure of the quality of the flow estimate provided by Meta-Facebook and related to the uncertainty behind the user count of the flow as described in Section 3; Popi,j represents the population at the origin (i) and destination (j) tiles; are parameters to estimate in the model linking their respective covariates to μijw; D is a trend tracking the day to which the flow relates to during the period in analysis; while Wk and H are indicator variables capturing day of the week (i.e., weekday or weekend) and hour window (i.e., 00:00–08:00, 08:00–16:00 and 16:00–00:00). Our focus in Equation (2) is centred on . Controlling for all other variables, these parameters capture the extent to which, the expected flow between a given origin-destination population density class pair of tiles (e.g., a high-density origin to a low-density destination) is systematically higher or lower than if it occurred between a baseline origin-destination population density class pair of tiles (e.g., a low-density origin to a low-density destination). Additionally, we standardised continuous variables (dij, qijw, Popi j), so that they can be interpreted as the expected flow on the first day (D=0), during the first temporal window (H=00:00–08:00), on a weekday (Wk=0), for the baseline origin-population population density class pair, when all the other variables are at their mean value. In this context, each can also be seen as the 'modulation factor' around that expectation associated with each pair of origin-destination classes. The baseline origin-destination population density class pair is the lowest population density class as origin and destination.

We used a count data regression model. Specifically, we fitted a generalised linear model (GLM) where the error term is assumed to be distributed following a Poisson distribution, with a flow expectation of (μijw) linked to the flow count (Fijw) through a log link: (3) (4) The Poisson regression model (PRM) assumes that equidispersion, that is, equality of mean and variance in the response variable (Cameron & Trivedi, 2013). In practice, the equidispersion property is commonly violated because of overdispersion, that is, the variance exceeds the mean. When this occurs, the PRM may produce biased parameter estimates, causing the standard errors of the estimates to be underestimated, and compromising the statistical inference process (Hilbe, 2011). To test for overdispersion, we used a regression-based test based on an auxiliary regression of the conditional variance as described in Cameron and Trivedi (2013).

Following Gelman and Hill (2006), we used a quasi-PRM to address overdispersion in our response variable. This is one of the most common strategies to deal with overdispersion in count data models (Hilbe, 2011). Intuitively, this model adjusts the standard errors of the estimates to account for the extra dispersion in the data. To implement this, we estimated Equation (2) by using robust variance estimators. The number of active Facebook users were used as a weight to account for the variability of the observed count of population movement over time. This strategy is also used to mitigate for any potential biases regarding the variation in the observed number of active Facebook users changes over time across Britain.

We fitted Equation (2) using iteratively reweighted least squares (IWLS). We separately estimated models for individual months in our data, resulting in 18 sets of estimates. Our key aim was to generate estimates for and , so that we focused on discussing the evolution of these estimates in a grid of line plots with 10 rows and 10 columns, each of them representing one of our population density classes. The plot corresponding to the Ith row and Jth column displays the evolution of the parameter that tracks the intensity of population flows from tiles in population density class Ith to those in population density class Jth.

5. Results

6. Discussion

7. Conclusion

8. References

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